CORPORATE STRATEGIES OF DIGITAL ORGANIZATIONS

by

Anparasan Mahalingam

A Dissertation

Submitted to the Faculty of Purdue University

In Partial Fulfillment of the Requirements for the degree of

Doctor of Philosophy

Krannert School of Management

West Lafayette, Indiana

August 2021

THE PURDUE UNIVERSITY GRADUATE SCHOOL
STATEMENT OF COMMITTEE APPROVAL

Dr. Richard Makadok, Chair
Krannert School of Management, Purdue University

Dr. Tony Tong, Chair
Leeds School of Business, University of Colorado Boulder

Dr. Stephen Martin
Krannert School of Management, Purdue University

Dr. Luis Rios
Krannert School of Management, Purdue University

Dr. Todd Zenger
David Eccles School of Business, University of Utah

Approved by:
Dr. Yanjun Li

To Appa and Amma – For shaping my intellectual journey.

ACKNOWLEDGMENTS

My PhDs (it still feels quite ironic to say PhD in plural) at Purdue University are a culmination of myriad learnings from so many people from all walks of life. For years, I had a vague idea that engineering and hard technological advancements will benefit from a systematic interface to both business strategy and public policy. Both my PhDs at Purdue are, in essence, operationalizing this idealistic and imprecise notion into specific coherent dissertations. Although, *ex post,* they look relatively cogent, my dissertation path had been messy, and as in the words of Bruce Springsteen it often felt like I, "[..] ain't learnin'; [..]; One step up and two steps back".

It was made possible because I had the world's best experts as my advisors on the topics I pursued, who also happened to be some of the most generous people I met in my life. Prof. Richard Makadok, my primary resident advisor at Purdue moved mountains both academically and administratively to make my strategy PhD work. From what I know, I am the second person to pursue two independent PhDs in parallel track at Purdue, and the first one was featured in the New York Times as he happened to be also the first one in the entire United States to do so.[1] I am exceedingly thankful for Rich's wise counsel and consistent support without which none of this would have happened. Prof. Tony Tong, co-chair of my dissertation, had been exceptionally helpful in shaping my thinking and developing me intellectually as a scholar. Tony had a sharp eye towards the habitual pitfalls PhD students fall into, so he helped me identify and avoid them while nurturing an ambitious research agenda together. It was in Prof. Steve Martin's Advanced Industrial Organization class I first read all the classics of two-sided markets and it was

[1] https://www.nytimes.com/1994/08/08/nyregion/purdue-student-in-a-first-earns-a-double-doctorate.html

foundational to developing my research. I had the wonderful opportunity to chat with Prof. Todd Zenger early in my PhD at a conference where he advised me to carefully think about digital organizations with core strategy questions in mind (in his words, “there cannot be two theories of firms in equilibrium, one for traditional organizations and the other for digital ones”). From then, Todd has guided me consistently to build a research agenda that would be core to corporate strategy and organizational governance research. Prof. Luis Rios, as a relatively junior professor compared to rest of the committee, provided me with distinct insights on the trends in the field and with advice on how I should approach them. Outside my dissertation committee, Prof. Mohammad Rahman from MIS has been an excellent mentor helping with research ideas and keeping me up to date with developments in economics of digitization. There is an ancient mantra in South Asia on “guru” – teacher – pronounces that a guru creates knowledge, preserves it and dispels the darkness of ignorance in a student. I am so humbled and honored to have had all these gurus during my dissertation process. I look forward to continuing to learn from all of them.

Growing up in Jaffna peninsula of Sri Lanka during the peak of civil war misfortunes were plenty, except for two: the abundance of intellectually sound education and a closely knit love-filled family. My parents inculcated the value of education in us; it was the single most important hope that guided all five of us brothers through the turbulent period. My father’s mental cookbook was that education combined with strong ethics would serve as the lighthouse for his sons in any stormy waters of life. While I will miss him dearly in all the years to come, I aspire to stay true to his philosophy of life in being daringly honest, intellectually curious and devoted to educating the future generation. I am also very grateful to my mother who despite very limited resources instilled strict discipline, and with a steady hand helped all of us “stay the course”. To all my brothers, Aravinthan, Arivu, Iniyan and Alagan, for sharing all the joys and grief in life together – I am infinitely stronger because of you.

I have been blessed to attend intellectual powerhouses since childhood - Jaffna Hindu Primary School and College, University of Peradeniya, United Nations University and Purdue University. In all these wonderful institutions, I have benefitted tremendously from my mentors and peers. Many of those relationships are close to my heart and will remain so for the rest of my life. Several colleagues I met during my time at Purdue made this long and often isolated Ph.D. experience a cherished one. I would like to thank all my strategy area PhD colleagues and many others both at IE and Krannert. I will also gratefully remember the times I spent together with some of my wonderful friends, Abhishek, Adarsh, Amir, Chao, Goran, Kubilay, Logan, Prasad, Rama, Sandi, Utsav, Vandith, Yanbing and so many others. I look forward to many more years of friendship with you. As for Mohammed, my PhD life would have been incredibly poorer without your presence (also sharing the Krannert 532 office for a good portion of time) to chat about NBA, Larry David, research and so much more. I am indebted to your camaraderie; thank you for being my best friend during our shared PhD time.

My immense gratitude goes out to my wife, Azrah Anparasan, who had been with me almost all my adult life, for all these cherished years together. She stood like a rock when the days were short and nights were long during these laborious PhDs. I hope our son, Aanma Rumi Mahalingam, will be able to look up to his parents and be proud of the journey we took together.

TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

ABSTRACT

This dissertation examines the implications of digitization for firm corporate strategy and organizational governance. I aim to link together emerging research on platform businesses and classic corporate strategy research on firm scale, scope and organization, two important streams of work that have remained largely independent despite the close connection between them. To do so, my dissertation revolves around the following central question: How can platform owners leverage governance mechanisms to alleviate market frictions, and what are the performance outcomes?

In the first chapter, using game-theoretic formal models, I analyze how long standing information frictions are alleviated by digital platforms through developing capabilities for solving these information problems and exploiting synergies between those capabilities. In the second chapter, using data from online peer-to-peer lending, I show that platform owners can mitigate problems of information asymmetry in platform markets and enhance market effectiveness through allocation of key decision rights among participants. Finally, in the third chapter, using data from mobile apps, I show that platform gatekeeping serves as a screening mechanism for platform owners and how it can shape the different ways app developers profit from innovation.

Collectively, my dissertation aims to advance corporate strategy research in two ways. First, my research broadens the application of theories of organizational governance core to corporate strategy to a new organizational form – platforms – and I show that core tenets of the theories still apply, although the specific empirical mechanisms might take a different form in the platform context (e.g., decision rights allocated between the platform owner and complementors, rather than between the corporate office and business units). Second, my research stands to expand existing

theories in corporate strategy through a sharp focus on organization and governance features that are unique to platforms – such as by studying the orchestrating role of the platform owner (e.g., through gatekeeping, platform owner can control complementors' platform access and shape their value-creation activities on the platform), and the multi-layer relationships prevalent in platforms (e.g., relationships between the platform owner and complementors, between complementors on the same side, and between complementors across two or more sides).

CHAPTER 1. INTRODUCTION

This dissertation examines the implications of digitization for firm corporate strategy and organizational governance. I aim to link together emerging research on platform businesses and classic corporate strategy research on firm scale, scope and organization, two important streams of work that have remained largely independent despite the close connection between them. I hope to highlight several ways in which classic corporate strategy research can enhance our understanding about the emerging platform phenomenon, and how it can be expanded by incorporating some of the distinctive features of this new organizational form. This has led me to develop a novel stream of research in this dissertation bringing together literatures on strategic management, entrepreneurship and organizational economics.

My dissertation revolves around the following central question: How can platform owners leverage governance mechanisms to alleviate market frictions, and what are the performance outcomes? Theoretically, I use analytical models to study how longstanding information frictions are alleviated in platform-based businesses through developing capabilities for solving these information problems and exploiting synergies between those capabilities. Empirically, using data from online lending and mobile apps, I investigate how platform owners' governance and design choices, such as decision rights allocation, priority access, gatekeeping, and resource support can mitigate potential hazards that surround economic exchanges between complementors, shaping platforms' performance and complementors' innovation.

Collectively, my dissertation aims to advance corporate strategy research in two ways. First, my research broadens the application of theories of organizational governance core to corporate strategy to a new organizational form – platforms – and I show that core tenets of the theories still apply, although the specific empirical mechanisms might take a different form in the platform context (e.g., decision rights allocated between the platform owner and complementors, rather than between the corporate office and business units). Second, my research stands to expand existing theories in corporate strategy through a sharp focus on organization and governance features that are unique to platforms – such as by studying the orchestrating role of the platform owner (e.g., through gatekeeping, platform owner can control complementors' platform access and shape their value-creation activities on the platform), and the multi-layer relationships prevalent in platforms (e.g., relationships between the platform owner and complementors, between complementors on the same side, and between complementors across two or more sides).

My dissertation explores these questions in three related studies. The first essay, *"Value Creation and Capture in Platform Business Models: An Information Theoretic Perspective"* (joint with Professor Richard Makadok), theoretically analyzes how platform-based businesses create and capture economic value by lubricating longstanding frictions in markets. My theoretical model analyzes three classic information-economics frictions – namely, coordination costs, search costs and transaction costs – and examines how demand-side synergies among the capabilities (that emerge from superior solutions to one or more hazards resolved simultaneously to heterogeneous consumers on a common platform with positive externalities) for addressing the three problems can help a platform create competitive advantage over rival platforms or non-platform substitutes. I further identify four different mechanisms, hidden action, hidden knowledge, preference heterogeneity and capacity constraints, and show how they create several contingencies shaping platforms' ability to address market frictions.

In the second essay, *"Decision Right Allocation and Platform Market Effectiveness: Evidence from Online Peer-to-Peer Lending"* (joint with Professor Tony Tong), proposes that platform owners can mitigate problems of information asymmetry in platform markets and enhance market effectiveness through allocation of key decision rights among participants. I link decision right allocation to the governance role platform owners play, arguing that they can orchestrate the participation of complementors by establishing particular governance rules. Employing a quasi-experimental design in online peer-to-peer lending involving Prosper.com and LendingClub.com, I show that reallocation of the pricing right (right to set loan interest rates) to the platform owner increases platform market effectiveness (rate of loan requests being funded by lenders). Further, this effect is strengthened by the financial information available in local environments, highlighting the role of the connection between online and offline information in shaping platform market effectiveness.

The third essay, *"Does Platform Gatekeeping Affect Complementors' Strategy to Profit from Innovation?"*, argues that platform owners can leverage gatekeeping as a governance instrument to mitigate information asymmetry, which in turn shapes the viability of complementors' appropriability regimes and strategies to profit from innovation. Exploiting the iOS 10 jailbreak to Apple's ex ante gatekeeping as a quasi-experimental design in the mobile app industry, we show that weak platform gatekeeping reduces complementors' opportunities to appropriate value before a user has experienced the products, and must resort instead to ex post monetization methods like initial free trials, freemium, or advertising support. We argue that platform gatekeeping has two effects on complementors' strategies for value appropriation: First, by mitigating adverse selection problems for users, gatekeeping raises users' willingness to pay for a complementor's products. Second, since gatekeeping provides a form of screening by the platform, it alleviates the need for users to conduct their own separate screening of complementors' offerings.

In conclusion, this dissertation builds on the classical notion that corporate strategy and the mechanisms of organizational governance are what make the corporate whole add up to more than the sum of its individual parts. The thread that unifies my intellectual pursuits is my goal for conducting cumulative high-quality research that can improve our knowledge of the fundamental issues in corporate strategy, by focusing on the effects of the ongoing digital transformation enabled by the internet technology and mobile telecommunications revolutions.

CHAPTER 2. VALUE CREATION AND CAPTURE IN PLATFORM BUSINESS MODELS: AN INFORMATION-THEORETIC PERPECTIVE

"Let's take just a moment together and appreciate just how amazing the internet is. You can use it to file your taxes, apply for jobs. You can go online right now and buy a case of coyote urine. Do you know how difficult it used to be to obtain coyote urine? You literally had to give coyote Gatorade and just wait. It was a mess. The system was a mess."

– John Oliver, *Last Week Tonight,* HBO (2014)

2.1 Introduction

The global economy of the early twenty-first century has been transformed by the proliferation of platform-based business models exploiting the revolution in information technology and mobile telecommunications of the late twentieth century, as shown in Figure 2.1. Among the world's eight largest companies by market capitalization in 2008, only one was a platform-based business. By 2019, that number had climbed to seven. Understanding this dramatic transformation presents a challenge to Resource-Based Theory (RBT), which is primarily concerned with how firms create value and how they can ensure that they capture some of the value that they create (Barney, 1991; Helfat & Peteraf, 2003; Wernerfelt, 1984). From a resource-based perspective, this recent proliferation of platform business models raises the question of how these business models affect the creation and capture of value.

Some researchers have begun to examine how platform businesses work (Adner, 2017; Boudreau, 2010; Jacobides *et al.*, 2018; Parker & Van Alstyne, 2005) and have offered a diverse range of notions to describe the value proposition behind platform-based business models. As in the legend of the blind men defining an elephant differently depending upon which part of the animal each one happened to touch, these divergent definitions of the platform phenomenon leave us without a clear unified overall picture. More economics-oriented research has discussed the importance of network effects (Hagiu & Wright, 2015; Parker & Van Alstyne, 2005; Rochet & Tirole, 2003) and how platform intermediation in two-sided or multi-sided markets often lead an arrangement where “the decisions of each set of agents affects the outcomes of the other set of agents” (Rysman, 2009). Both direct network effects (agents benefiting from increasing similar type in the same-side of the market) and indirect network effects (agents benefiting from increasing complementary type in the other side of the market) create value in the market (Eisenmann *et al.*, 2011; McIntyre & Srinivasan, 2017; Shapiro & Varian, 1998). Another stream of research has advanced an ecosystem perspective. One set of arguments within this tradition focuses how platform owners orchestrate the participation of complementors in the ecosystem and how that can lead to the creation of value (Boudreau, 2017; Jacobides *et al.*, 2018). Another set of arguments focus more on getting the “alignment structure” right for the “multilateral set of partners that need to interact in order for a focal value proposition to materialize” (Adner, 2017; Adner & Kapoor, 2010). Some others have provided technically oriented definitions to platform business models. For example, Tiwana *et al.* (2010) define platforms as the “extensible codebase of a software-based system that provides core functionality shared by the modules that interoperate with it and the interfaces through which they interoperate”. Here the potential for new business models emerge from the robust technical base of platform (Boudreau, 2012; Ghazawneh & Henfridsson, 2015). Researchers have also emphasized some specific features of the platforms that provide the genesis for a value proposition. They include, but not limited to, efficient digital matching (Einav *et al.*, 2016; Fradkin, 2017), resolving bottlenecks between components (Hannah & Eisenhardt, 2018), providing reputation mechanisms (Forman *et al.*, 2008; Hosanagar *et al.*, 2013) and improved targeting and tracking of customers (Athey *et al.*, 2013; Goldfarb & Tucker, 2011).

Notwithstanding John Oliver's lament about the former travails of obtaining coyote urine in bygone days, analog predecessors of today's global mobile digital platforms have nevertheless existed for centuries, at least as far back as Medieval fairs in the Champagne region of France (Fisman & Sullivan, 2016: chapter 6) and their counterparts in Turkish and Persian bazaars and elsewhere, including trading posts along Asia's Silk Road. Yet these historical platforms never grew to dominate the global economy in the same way as today's, and this fact offers a clue about how any platform – past, present, or future – creates and captures value. As Sherlock Holmes started one murder investigation by asking what the dog did during the night and surprisingly found that the answer was nothing – a clue that ultimately led him to the culprit – one might similarly ask why platform organizations did so little before the twenty-first century. Or, conversely, one might ask what does the digital technological revolution allow platforms to do at large scale that they previously could only do at small scale? So, because recent technological developments merely enhanced platform business models (albeit quite dramatically) rather than outright creating them *de novo*, we eschew technology-based explanations of platform businesses (e.g., Tiwana *et al.*, 2010) as insufficiently fundamental to capture the true elemental core of the phenomenon.

Instead, we focus on the underlying economic problems that platforms have solved throughout history. Mahoney (2001) argues that a necessary condition for a firm to capture sustainable rents is that there must be sufficient market frictions to justify performing some transaction within an organizational hierarchy, rather than via a market contract (see also Bel, 2018; Mahoney & Qian, 2013). A corollary to this idea is that, conversely, any firm with seemingly "sustainable" rents is vulnerable to disruption by a platform that can lubricate these market frictions away. Our premise is that platforms, in their analog form, have always created value by lubricating market frictions due to information problems, but that today's combination of inexpensive information technology and mobile telecommunications now enables digital platforms to lubricate these longstanding frictions on a grand scale, for innumerable buyers and sellers, and to do so across a limitless variety of markets, no matter how small or obscure they may be (e.g., even the market for coyote urine).

This paper seeks to understand the patterns in the specific types of information problems that platforms solve in their efforts to create and capture value. There are three classic information problems in economics – coordination problems, search costs, and transactional hazards. We observe (see the next section for details) that different platform-based businesses aim to solve different combinations of these three problems. Some are specialists that solve only one, while others solve two, and a few generalists solve all three. Why do these differences between platforms occur? We also observe a pattern of platforms trying to increase the number of information problems that they solve over time, as in Apple adding the App Store to its platform about one year after launching the iPhone, or Amazon's launch of Amazon Marketplace and Amazon Pay. Why does this trend toward greater diversification of activities occur?

Conventional corporate-level resource-based logic would suggest that decisions about specializing on a single activity versus diversifying across multiple activities may be driven, at least in part, by the pattern of synergies between the activities. So, as a starting point, we need some theory to predict the conditions under which each of these three value-creation mechanisms are synergistic with each other, and the ways in which they may be counter-synergistic. Existing research indicates that supply-side synergies – i.e., economies of scope – can reduce the cost of combining information collection, storage, analysis, and dissemination across multiple functions (Brynjolfsson & Kahin, 2002; Dawson *et al.*, 2016; Goldfarb & Tucker, 2019; Shapiro & Varian, 1998), but little attention has been given to demand-side synergies across the various functions of a platform. Therefore, we develop a formal model to examine how demand-side synergies arise between these three mechanisms. Our model combines simple versions of three classic canonical information-theoretic models – coordination, search, and agency – in order to examine the synergistic interactions among the capabilities to reduce them, and to identify limits on those synergies. One such limit arises because lubricating information-based frictions inherently requires that platforms must necessarily gather, store, analyze, and disseminate information about users, often in ways that invade or threaten their privacy. So, just as information may be synergistic in lubricating multiple frictions simultaneously, our model also explores how the reverse can also occur as users' privacy sensitivity may reduce, eliminate, or even reverse these synergies.

Our model produces two potentially useful insights for the strategy scholars and managers alike. First, it shows that when privacy concerns are sufficiently weak, positive synergies across the solutions for all three informational frictions are achieved, thereby providing an incentive for some platform-based firms to expand their business models to become generalists by solving more informational problems – e.g., the launch of Amazon Marketplace and Amazon Pay. Second, our model elucidates the limiting upper thresholds on these synergies due to the privacy concerns that are inherently baked into platform business models, thereby providing an incentive for some platform-based firms to remain specialists in solving a single informational problem – e.g., Craigslist's abdication of responsibility for policing transactions, or DuckDuckGo's commitment to never collect data on users of its search engine.

The remainder of this paper is organized as follows: We start with a typology of the information problems underlying market frictions, followed by a discussion of how platform business models can both develop capabilities for solving these information problems and exploit synergies between those capabilities. We then present our formal model, starting with the assumptions and a two-player case to establish how the two sides of the market would perform without the assistance of a platform as intermediary between them. Then we present the full three-player version of the model with platform as intermediary. The difference between this full three-player version and the two-player case enables us to identify the marginal value added by the platform and the cost implications associated with this value creation process. From this we derive propositions about the synergies between capabilities to solve different information problems (i.e., to lubricate different frictions). We then extend the model to include privacy concerns as a limiting factor that constrains the magnitude of these synergies and may even generate counter-synergies, and we develop propositions about these effects. Finally, we conclude with a discussion on broader implications of our contribution.

2.2 Information Problems, Market Frictions, and Platform Models: A Typology

As mentioned in the previous section, and as shown in Figure 2.2, there are three classic information problems in economics that can be responsible for market frictions – coordination problems, search costs, and transactional hazards. Let us consider each of them in turn.

Perhaps the most fundamental of these frictions is the coordination problem, where it is necessary to choose one of several possible methods for buyers and sellers to interact, and the buyers have different preferences about these methods than sellers (for a review of coordination games, see Cooper, 1999). For example, in the case of transactions that require face-to-face interactions – e.g., personal services like hair styling, or types of merchandise that buyers must inspect before purchasing – buyers and sellers must physically appear in the same place at the same time, and if buyers have different preferences about these places and times than sellers, then where and when will they meet? Which side will adapt its schedule and transportation arrangements to suit the other? In this regard, one of the most fundamental benefits of the Medieval fairs of France was to specify a standard set of dates and locations. Likewise, if buyers speak a different native language than sellers, then which side will accommodate the other by learning a foreign tongue? Differing information-processing and communication protocols provide a modern version of this language-barrier problem. For example, different types of microprocessors can differ in the instruction sets that they are able to interpret (e.g., CISC vs. RISC), and different types of operating systems (e.g., Android vs. iOS) can differ in their protocols for managing application software and allocating system resources, so software written for one type will not run on another. If each computer had its own unique instruction set or its own unique operating system, then all software – even the most basic features – would have to be laboriously custom-programmed. Coordination problems are especially difficult when the preferences of each side are strong, when the costs of accommodating the other side are high, and when it is impractical to use side payments to motivate either side to accommodate the other (e.g., when sellers and buyers are both diffuse groups that cannot easily cooperate on a collective action). A good solution to a coordination problem would overcome individual preferences to reach accommodation, but this requires some players to make a sacrifice that benefits others. Some platform business models seek to solve coordination problems via standards that specify how, when, and where the two sides interact – e.g., in terms of time, physical location, virtual location, language, measurement unit, interaction procedure, processing method, communication channel, or communication protocol.

Search problems, another type of market friction, commonly occur under horizontal differentiation – i.e., when there are heterogeneous offerings between the players on one side, usually the sellers, and heterogeneous preferences between the players on the other side, usually the buyers (Diamond, 1971; Roth & Sotomayor, 1992; Stigler, 1961). For example, restaurants differ in the spiciness of their food and customers differ in their preferences for spice. Search problems are especially difficult when heterogeneity on both sides is large, when players' types are unchangeable, when information about each player's type is private, and when it is costly for a player on either side to learn the type of a player on the other side. A good solution for a search problem would match each buyer with a seller that can satisfy his or her preferences well. Such matching allows buyers and sellers to find and identify each other when they otherwise could not. Some platform business models seek to solve or mitigate search problems via categorization (Craigslist), curation (Steam), database query (Google), matching algorithms (eHarmony), or recommendation engines (Netflix).

Finally, transactional hazards occur when a player on one side of the market, usually the seller, has superior private information about the quality or value of the good or service, which is not observable by players on the other side of the market, usually buyers (Akerlof, 1970; Grossman & Hart, 1983; Rothschild & Stiglitz, 1976; Spence, 1973). Transactional hazards may be in the form of either moral hazard, where the seller can influence the quality or value, or adverse selection, where the seller has no such influence. In extreme cases, such information asymmetry can cause not only market frictions but actual market failure, when opportunistic sellers and cautious buyers cannot agree on a price. Transactional hazards are especially difficult when uncertainty is high and when the information asymmetry is severe and costly to remedy through monitoring or inspection. A good solution for a transactional hazard would be a mechanism that either reveals private information directly or motivates the side with private information to either take actions in the other side's interests (e.g., performance-based compensation) or choose to reveal the private information (e.g., risk-sharing techniques like warranties or deductibles). These mechanisms substitute for interpersonal trust, by allowing a buyer to trust the transaction even when they cannot trust the seller. Some platform businesses seek to solve or mitigate transactional hazards via escrow, bonding, monitoring, testing, inspecting, certification, dispute resolution procedures, or publishing user ratings or reviews.

2.3 Resources and Synergies for Mitigating Market Frictions

As shown in Figure 2.3, platform businesses differ in the types of market frictions that they mitigate because different platforms aim to solve different combinations of informational problems. While some specialist platforms focus on a niche by solving only a single narrowly-defined information problem (Anderson & Andersson, 2004; Brynjolfsson *et al.*, 2006), other generalist platforms solve multiple information problems, often expanding well beyond their original business models in order to do so (Noe & Parker, 2005; Schmalensee & Evans, 2001).

As an example of a specialist focusing on a single market friction, Craigslist only tries to solve the search problem by matching buyers and sellers with each other, but makes no attempt to coordinate when or where buyers and sellers should meet to complete their exchange, and offers no method for mitigating transactional hazards. Likewise, PayPal only tries to solve a transactional problem by guaranteeing prompt payment to a seller while simultaneously protecting the buyer by keeping his/her payment account numbers confidential, but PayPal makes no effort to help buyers and sellers find each other, nor makes any attempt to coordinate how buyers and sellers interact with each other in terms of completing their exchange. The Windows 95 platform only solved a coordination problem by setting a standard for how users interact with content created by software developers and vice versa, but it did not help users in their search for software to suit their unique needs, nor did it provide any guarantee that software would work as advertised or that software developers would be paid.

By contrast, other platforms aim to solve two information problems simultaneously. For example, Angie's List solves both search and transactional problems by enabling homeowners to find relevant home-improvement contractors while also providing ratings and reviews of those contractors, but makes no attempt to coordinate details of how or when the home improvements are to be completed. Uber solves the same two informational problems – matching riders and drivers by their location and availability, and de-hazarding the transaction by publishing ratings that riders and drivers give each other, but never coordinating the details of how riders and drivers interact during the ride itself. For solving a different pair of informational problems, a low-tech example is a shopping mall, which both coordinates buyers and sellers by standardizing the location and times where they can meet and helps buyers find sellers by providing directories of its stores on its signs and in its pamphlets, but provides no guarantees for either the quality of its sellers' merchandise nor for the trustworthiness of its buyers' payments. Even the Medieval fairs in Champagne solved two informational problems – serving both a coordination function by specifying the dates and locations where buyers and sellers could meet and a de-hazarding function by bringing a court-like system to those locations for dispute resolution, but providing no guidance to help match particular buyers to particular sellers or vice versa.

Finally, a few platforms lubricate all three frictions, such as Amazon's Kindle e-book platform. On the coordination side, Kindle defines standard file formats and communication protocols by which the publisher's content interacts with the reader's device. On the search side, Kindle's recommendation engine helps readers find books that suit their particular interests. On the transaction side, Amazon's payment system and Kindle's digital rights management system ensure that the publisher gets paid for every sale and protected from unauthorized book copying by readers, while Kindle's rating and review system alerts readers about the quality of books.

Why do different platforms vary so widely in the range of frictions that they lubricate, as illustrated in Figure 2.3? We view this breadth of informational activities as a scope decision, similar to other classic scope decisions or firm boundary decisions that have long been considered by corporate-level resource-based theory – e.g., product market entry/exit, product line breadth, geographic diversification, vertical integration, or outsourcing. Such corporate scope decisions are often intertwined with how corporate strategies can facilitate efficient allocation, development, reconfiguration and redeployment of resources (Helfat & Eisenhardt, 2004; Levinthal & Wu, 2010; Montgomery, 1994; Sakhartov & Folta, 2015; Teece *et al.*, 1994). Corporate strategy theory suggests that scope decisions are driven, at least in part, by resources that generate synergies across different existing and possible businesses (Ahuja & Novelli, 2017; Feldman, 2019; Karim & Kaul, 2014; Sakhartov & Folta, 2014; Zhou, 2011).

For this reason, understanding firms' scope decisions requires knowing what resources underlie the synergies, where and how the resulting synergies arise, and what the limits of those synergies are. For example, some synergies arise on the supply side in the form of cost-reducing economies of scope (Panzar & Willig, 1981; Teece, 1980), while others arise on the demand side (Lemelin, 1982) in a variety of forms such as reduced shopping costs for the buyer (Klemperer & Padilla, 1997), or greater customer willingness to pay due to either better integration across products (Stremersch & Tellis, 2002), or improved customer productivity (Hinterhuber, 2002), or customer knowledge that spans product categories (Chatain, 2011; Nayyar, 1990, 1993).

With regard to platform-based business models, especially the modern digital types, it is already well understood that platforms benefit from substantial scope economies on the supply side (Brynjolfsson & Kahin, 2002; Dawson *et al.*, 2016; Goldfarb & Tucker, 2019; Shapiro & Varian, 1998). For example, in a thorough review of digital economics, Goldfarb and Tucker (2019) emphasized how the ability to represent information in bits reduces the cost of storing, processing and transmitting the data. They emphasize, on the supply-side, while platform-based business models fundamentally do not require new economic theory, they require a different emphasis. These falling supply-side costs help with low-cost mobilization of resources, and when aggregated into executing functions of business models, offer superior avenues to solve information problems (Ellison & Ellison, 2005; Goldfarb & Tucker, 2019; Shapiro & Varian, 1998). However, despite the wealth of knowledge about platforms' supply-side synergies, much less is known about demand-side synergies, especially synergies between demand for lubricating the three types of market frictions. Therefore, our model focuses on this particular issue.

When defining what demand-side synergies means for a platform-based business, we must first pause to define what demand itself means for a platform-based business. The distinctive feature of platform-based business models – sometimes called "two-sided" or "multi-sided" markets – is that they necessarily serve at least two distinct customer constituencies who create value via some interaction with each other. To succeed, a platform must satisfy constituencies on both (or all) sides of the market – i.e., "demand" for a platform's services must arise simultaneously, in appropriate proportions, from two or more sources. Logically, the value added by a platform depends upon how much more value those constituencies can create with the assistance of the platform as an intermediary between them, over and above the value that they could create for and by themselves in the absence of the platform. This added value, we contend, is the result of lubricating market frictions that arise from the three classic informational problems. So, demand for a platform's services means demand for this lubrication. Therefore, we define demand-side synergies for platform businesses as the synergies between the three forms of lubrication – i.e., synergies between demand for solving coordination problems, demand for reducing search costs, and demand for de-hazarding transactions.

2.4 Baseline Model Without Privacy Concerns

We start with a baseline version of the model to demonstrate that all three platform functions are synergistic with each other in the absence of privacy concerns.

2.4.1 Definition of the Players in the Market

We assume that there are two sides of the market, which we label as principals (denoted P) and agents (denoted A). In most cases, one can think of principals as representing the demand side of the market and the agents as representing the supply side, but there may be situations where these roles are reversed. For the purposes of our information-economics model, what matters is who knows what, not who pays whom, so we avoid terms like buyer, seller, consumer, or producer.

Our simplifying assumption that there are only two sides of the market restricts the applicability of the model somewhat, since it excludes more multi-sided markets – e.g., the relationship between app developers, advertisers, and users in platforms with advertising-supported apps. Likewise, our assumption of a unidirectional agency relationship with principals on one side of the market and agents on the other side also restricts the applicability of the model somewhat, because it excludes situations where the agency relationship is more bidirectional in nature – e.g., dating platforms. The third player is, of course, the platform itself (denoted I for "intermediary"). To keep this initial modeling exercise simple and tractable, we assume that there is only one platform, and we leave the challenge of modeling competition between platforms to future research. However, as a "do it yourself" form of competition, we assume that the principals and agents could choose the disintermediation option of cutting out the middleman and conducting their interactions and transactions outside of the platform. Indeed, we calculate the platform's value added (and captured) relative to this no-platform disintermediation option.

2.4.2 Overview of Model Timing

We use a three-stage model, corresponding to the three informational frictions that the platform can lubricate. We arrange the three stages in the most natural sequence: Coordination must come first. If the principals and agents do not share some common channel, method, or venue for interacting, then they cannot find each other to solve the search problem, and they cannot conduct a transaction to create value. For example, a Medieval textile buyer (or his/her representative) would first have to be in the same location where there are textile sellers (or their representatives) before he/she could find the right merchandise, inspect it, and make a purchase. Likewise, searching for, buying, and downloading iPhone apps requires that one must first actually own an iPhone. Once some set of principals and agents have been coordinated on the same channel, method, or venue for interacting, they can then be matched with each other. Only then, after a particular principal has been matched to a particular agent, can these two parties then actually conduct the transaction to create some value. The particular principal and particular agent cannot transact until they have been matched to each other. So, the sequence of stages in our model is coordination first, then matching, then transaction. These three stages can be performed either with or without the assistance of a platform as intermediary, and we compare the results of those two possibilities to calculate the platform's value added. The detailed solution of the model via backward induction is provided in the Appendix. Here we simply summarize the assumptions for each stage and then report the overall results of the model.

2.4.3 Assumptions for the Coordination Stage

At the coordination stage, we envision a large set of principals and a large set of agents trying to reach an agreement about the channel, method, protocol, or venue by which principals will be able to interact with agents and vice versa. The coordination problem arises because the principals prefer a different channel, method, protocol, or venue than the agents prefer. Due to the large number of players on both sides (principals and agents), this disagreement cannot simply be solved via negotiation. For example, any negotiated side payment intended to bribe one side to adopt the other side's preferred standard would be undermined by free-rider problems on the side that is expected to make the payments.

So, the only choice available to each side is whether to accommodate (a) or not accommodate (n) the other side's preferred channel, method, protocol, or venue. If neither side accommodates the other, then no standard channel, method, protocol, or venue is adopted, in which case there is no way for principals and agents to be matched to each other, and no way for them to transact with each other, so zero value would be created, and there would be no value available for any player to capture. On the other hand, if either side chooses to accommodate the other, then a standard is adopted, so the players can then move on to the next stage of the model (matching). Let $y_{Pd} > 0$ and $y_{Ad} > 0$ represent the expected values that a typical representative principal and a typical representative agent, respectively, can anticipate capturing in the absence of a platform (using subscript d for "disintermediation") if a standard is adopted and the players move on to the next stage. Likewise, let $y_{Pi} > 0$ and $y_{Ai} > 0$ be the expected values that they can anticipate capturing with the assistance of a platform (using subscript i for "intermediation") if a standard is adopted and the players move on to the next stage. Let $\omega > 0$ represent the additional value that a typical agent receives if the principals accommodate the agents' preference, which is also assumed to be equivalent to the additional value that a typical principal receives if the agents accommodate the principals' preference. Thus, ω represents the (symmetric) strength of the two sides' intrinsic preferences about the choice of standard. Let $\mu > 0$ represent the cost a typical agent must pay to accommodate the principals' preference, which is also equivalent to the cost a typical principal must pay to accommodate the agents' preference. In order to guarantee gains to coordination, we assume that $\omega > \mu$; otherwise, neither side would ever accommodate the other. Table 2.1 shows the coordination game payoffs of a typical principal/agent pair. The total payoff for both sides is lowest when neither accommodates the other (n,n) and greatest when both sides accommodate each other (a,a). However, the latter outcome is not a Nash equilibrium, because each side has an incentive to unilaterally defect from its accommodation.

The coordination problem, as illustrated in Table 2.1, is that there are two pure-strategy Nash equilibria, each preferred by a different side. The principals prefer the (n,a) equilibrium where they are accommodated by the agents, while the agents prefer the (a,n) equilibrium where they are accommodated by the principals, and the inability to negotiate side payments leaves the two sides with no way to reach agreement on a single pure-strategy equilibrium. So, in the disintermediation scenario, without any other third-party coordination mechanism, the two sides can only reach a single equilibrium via mixed-strategy equilibrium, where each side chooses whether to accommodate randomly and independently. Equilibrium mixed-strategy probabilities for each side to accommodate the other are $p_{Pd} = 1 - (\mu/y_{Ad})$ for principals and $p_{Ad} = 1 - (\mu/y_{Pd})$ for agents, which yields expected payoffs for principals and agents, respectively, of:

$$E[U_{Pd}] = \frac{(y_{Pd}-\mu)(y_{Pd}+\omega)}{y_{Pd}} \quad and \quad E[U_{Ad}] = \frac{(y_{Ad}-\mu)(y_{Ad}+\omega)}{y_{Ad}} \qquad (1)$$

Expected welfare under this mixed-strategy equilibrium is just the sum of these two payoffs:

$$E[U_{Wd}] = E[U_{Pd}] + E[U_{Ad}] = y_{Ad} + y_{Pd} + 2(\omega - \mu) - (\mu\omega/y_{Ad}) - (\mu\omega/y_{Pd}) \qquad (1)$$

However, this mixed-strategy equilibrium may not be a particularly good solution because it has a probability of $\mu^2/y_{Pd}y_{Ad}$ for the worst outcome, where neither side accommodates the other.

Next consider how and when the mixed-strategy equilibrium can be improved by the platform intermediary (I) providing a third-party coordination mechanism. We use a variation of the Aumann (1974, 1987) correlated equilibrium where the platform plays the role of a signal generator whose capability can vary. The platform sends the principals one binary signal, labeled s_P, while simultaneously sending the agents a separate binary signal, labeled s_A. Each side can only observe its own signal, not the other side's. Each binary signal can take either the value a to ask that side to accommodate, or the value n to ask that side not to accommodate. So, the platform can send four possible signal pairs: $(s_P, s_A) \in \{(n,n),(a,n),(n,a),(a,a)\}$.

Our mathematical model represents each side's signal to a simple binary "a vs. n" bit of information, but in reality, these two possible messages differ greatly in their complexity. On one hand, communicating a message not to accommodate the other side (n) is quite simple; the only instruction is to do nothing new, and just keep doing what you wanted to do anyway. On the other hand, communicating a message to accommodate the other side (a) may be quite complex, since accommodating may involve adopting detailed technical protocols, following a particular schedule, or learning new jargon (or even a new language). Therefore, we assume that sending a signal to accommodate (a) requires the platform both to have greater communication capability and to pay higher cost than sending a signal not to accommodate (n).

First, consider the capability side. Taking parameter $\delta \in [0,1]$ as a measure of the platform's communication capability, the platform sends the signal pair (n,n) with probability of $p_{nn} = 1 - \delta$, signal pair (a,n) with probability of $p_{an} = g$, signal pair (n,a) with probability of $p_{na} = g$, and signal pair (a,a) with probability $p_{aa} = \delta - 2g$, where the variable $g \in [0, \delta/2]$ determines the relative frequency of signaling both sides versus only one side to accommodate and is endogenously chosen by the platform. As the platform's capability level δ increases, signaling the worst outcome for total payoffs (n,n) becomes less likely, while signaling the best outcome for total payoffs (a,a) becomes more likely. In order to guarantee that both sides follow the signals that the platform gives them, we assume that $p_{aa}(\omega - \mu) > p_{nn}(y_{Pi} + y_{Ai} + \omega - \mu)$ and $p_{nn} < \mu \min\{g/(y_{Ai} - \mu), g/(y_{Pi} - \mu)\}$. In order to guarantee that this correlated-equilibrium outcome dominates the mixed-equilibrium outcome, we also assume that $p_{aa} > p_{nn}$. In terms of capability parameter δ, all these assumptions can be combined into:

$$\delta > \max\left\{1 - \frac{\mu\, g}{y_{Ai}-\mu}, 1 - \frac{\mu\, g}{y_{Pi}-\mu}, \frac{1}{2} + g, 1 - \frac{(1-2g)(\omega-\mu)}{y_{Pi}+y_{Ai}+2(\omega-\mu)}\right\} \tag{3}$$

The resulting expected gross payoffs (i.e., payoffs before deducting the platform's fee) for the typical principal and agent, respectively, in this platform-intermediated scenario are:

$$E[U_{Pi}] = (\delta - g)(\omega - \mu) + \delta\, y_{Pi} \quad \text{and} \quad E[U_{Ai}] = (\delta - g)(\omega - \mu) + \delta\, y_{Ai} \tag{4}$$

On the cost side, we assume for simplicity that it costs the platform nothing to send the no-accommodation signal n, so the only cost is from sending an accommodation signal (a). Due to limits on communication capacity and bandwidth, assume the marginal cost of sending more accommodation signals increases in the frequency with which they are sent. So, the platform incurs quadratic costs of $c_I = [E(s_P = a) + E(s_A = a)]^2/2\eta = 2(\delta - g)^2/\eta$, where $\eta > 0$. In exchange for incurring these costs, the platform appropriates a share $\rho \in (0,1)$ of the value that it creates for the principals (i.e., the difference between a principal's gross payoff with versus without the platform) and the value that it creates for the agents (i.e., the difference between an agent's gross payoff with versus without the platform). So, the platform's expected payoff is:

$$E[U_{Ii}] = \rho\left(\delta(y_{Ai} + y_{Pi}) + 2(\delta - g)(\omega - \mu) - \frac{(y_{Ad}-\mu)(y_{Ad}+\omega)}{y_{Ad}} - \frac{(y_{Pd}-\mu)(y_{Pd}+\omega)}{y_{Pd}}\right) - \frac{2(\delta-g)^2}{\eta} \tag{5}$$

The platform maximizes this profit by selecting g, which involves a trade-off: Lower values of g raise the value added by the platform, but at the expense of incurring higher costs. In order to guarantee that the platform chooses a feasible value of g between zero and $\delta/2$, we assume that $\delta/\rho(\omega - \mu) < \eta < (1 + \delta)/\rho(\omega - \mu)$. Adding all three players' expected payoffs, welfare is:

$$E[U_{Wi}] = \delta(y_{Ai} + y_{Pi}) + 2(\delta - g)(\omega - \mu) - \frac{2(\delta-g)^2}{\eta} \tag{6}$$

2.4.4 Assumptions for the Matching Stage

For simplicity, we assume principals or agents who fail to find a successful match are unable to move forward into the transaction stage, and therefore terminate the game with a payoff of zero. For principals and agents searching for each other "in the wild" in the absence of a platform, we assume that a successful match occurs with probability of $(1+\theta)/2$, where $\theta \in [0,1]$. With the assistance of the platform, this probability increases to $[1+\theta(1-\tau)+\tau]/2$, where $\tau \in [0,1]$ is the platform's matching capability. As τ increases from 0 to 1, the probability of a successful platform-intermediated match increases from $(1+\theta)/2$ to 1. Let $z_{Pd} > 0$ and $z_{Ad} > 0$ represent the expected values that a typical principal and a typical agent, respectively, can anticipate capturing in the disintermediation no-platform scenario if they successfully match with each other and move on to the transaction stage. Likewise, let $z_{Pi} > 0$ and $z_{Ai} > 0$ be the expected values that they can anticipate capturing with the assistance of a platform in the intermediation scenario if they successfully match with each other and move on to the transaction stage. So, $y_{Pd} = z_{Pd}(1+\theta)/2$, $y_{Ad} = z_{Ad}(1+\theta)/2$, $y_{Pi} = z_{Pi}[1+\theta(1-\tau)+\tau]/2$, and $y_{Ai} = z_{Ai}[1+\theta(1-\tau)+\tau]/2$.

2.4.5 Assumptions for the Transaction Stage

Let the total value created for the principal be a weighted average of the agent's privately chosen effort level $e > 0$ and a normally-distributed random noise $X \sim N(0,1)$. We assume that the agent faces diminishing returns in generating effort, perhaps due to exhaustion or some other resource constraint, so that there are increasing marginal costs of exerting more effort. So, we use a quadratic cost of effort function of either $c_{Ai} = e_i^2/2\alpha$ in the platform-intermediated scenario, or

$c_{Ad} = e_d^2/2\alpha$ in the disintermediation scenario, where parameter $\alpha > 0$ represents the agent's efficiency. Neither the effort level *e* nor the random noise *X* are observable by the principal, nor by any other third party, so they are non-contractible. Only the total value created for the principal is contractible. In the disintermediation scenario without a platform, this total value created is $V_d = (1-\beta)e_d + \beta X$, where $\beta \in (0,1)$ represents the severity of the information asymmetry. As β increases, the total value created in the transaction becomes more a reflection of random noise, and less a reflection of the agent's effort. In the intermediation scenario, the platform reduces the information asymmetry by a proportion $\lambda \in (0,1)$, which represents the platform's de-hazarding capability, so that the total value created for the principal becomes $V_i = [1-\beta(1-\lambda)]e_i + \beta(1-\lambda)X$ instead. In effect, the platform helps the principal more clearly distinguish the agent's effort from the random noise. The principal motivates the agent by paying a wage that is linear in the total value created – i.e., $W_i = m_i V_i + b_i$ in the intermediation scenario, or $W_d = m_d V_d + b_d$ in the disintermediation scenario. The principal's payoff is $\Pi_{Pi} = V_i - W_i$ in the intermediation scenario, or $\Pi_{Pd} = V_d - W_d$ in the disintermediation scenario, with expected values of:

$$E[\Pi_{Pi}] = (1-m_i)[1-\beta(1-\lambda)]e_i - b_i \quad \text{or} \quad E[\Pi_{Pd}] = (1-m_d)(1-\beta)e_d - b_d \tag{7}$$

The agent's payoff is $\Pi_{Ai} = W_i - c_{Ai}$ in the intermediation scenario, or $\Pi_{Ad} = W_d - c_{Ad}$ in the disintermediation scenario. We assume that the agent has a reservation expected payoff of $\gamma > 0$ that must be satisfied in order for the agent to accept the contract – i.e., the agent's participation constraint. So, the agent's expected payoff, and participation constraint is:

$$E[\Pi_{Ai}] = (m_i[1-\beta(1-\lambda)]e_i + b_i) - (e_i^2/2\alpha) = \gamma \quad \text{or} \quad E[\Pi_{Ad}] = (m_d(1-\beta)e_d + b_d) - (e_d^2/2\alpha) = \gamma \tag{8}$$

The sequence of events in the transaction stage is as follows: First, the principal chooses the two contractual terms – the guaranteed base compensation *b* and the performance-linked incentive m – so as to maximize its own expected payoff, conditional on rational expectations about the effort the agent will exert under those contractual terms, and subject to the constraint of satisfying the agent's reservation expected payoff. We also assume whatever parameter constraints are necessary to ensure that the resulting expected payoff to the principal must be positive – i.e., the principal's participation constraint. Second, the agent privately chooses its effort level to maximize its own expected payoff under the agreed contractual terms. Next, the random value of the noise X is drawn, which determines the total value created for the principal. Finally, the principal pays the agent its wage as a function of that total value created.

2.4.6 Baseline Model Solution Via Backward Induction

We solve for the model's equilibrium via backward induction, starting at the end and working backward by using each stage's results as rational expectations to inform players' choices in the previous stage. We designate optimal values of each endogenous variable with an asterisk (*) superscript, and equilibrium values with a double asterisk (**) superscript. We first solve the disintermediated version without a platform, followed by the platform-intermediated scenario.

Disintermediation Scenario: Transaction Stage. The agent's optimal effort choice is $e_d^* = \alpha(1-\beta)m_d$. Substituting this into Equations 7 and 8 provides the principal's objective function and the agent's constraint. Maximizing this objective function subject to this constraint yields equilibrium contractual terms $b_d^{**} = \gamma - [\alpha(1-\beta)^2/8]$ and $m_d^{**} = 1/2$, which implies an equilibrium effort level $e_d^{**} = \alpha(1-\beta)/2$, equilibrium expected payoffs $z_{Ad}^{**} = E[\Pi_{Ad}^{**}] = \gamma$ and $z_{Pd}^{**} = E[\Pi_{Pd}^{**}] = [3\alpha(1-\beta)^2/8] - \gamma$, and a principal's participation constraint $\gamma < 3\alpha(1-\beta)^2/8$.

Disintermediation Scenario: Matching and Coordination Stages. Substituting the equilibrium expected payoffs from the transactions stage into the results for the prior stages yields $y_{Ad}^{**} = \gamma(1+\theta)/2$ and $y_{Pd}^{**} = ([3\alpha(1-\beta)^2/8] - \gamma)(1+\theta)/2$ for the matching stage, which in turn yields mixed-strategy equilibrium expected results from the coordination stage of:

$$E[U_{Pd}^{**}] = \frac{\left((3\alpha(1-\beta)^2-8\gamma)(1+\theta)-16\mu\right)\left((3\alpha(1-\beta)^2-8\gamma)(1+\theta)+16\omega\right)}{16(3\alpha(1-\beta)^2-8\gamma)(1+\theta)} \quad (8)$$

$$E[U_{Ad}^{**}] = \frac{(\gamma(1+\theta)-2\mu)(\gamma(1+\theta)+2\omega)}{2\gamma(1+\theta)} \quad (9)$$

$$E[U_{Wd}^{**}] = \frac{3\alpha(1-\beta)^2(1+\theta)}{16} + 2\left[\omega - \mu\left(1 + \frac{3\alpha(1-\beta)^2\omega}{\gamma(1+\theta)(3\alpha(1-\beta)^2-8\gamma)}\right)\right] \quad (10)$$

Intermediation Scenario: Transaction Stage. The agent's optimal effort choice is $e_i^* = \alpha[1-\beta(1-\lambda)]m_i$. Substituting this into Equations 7 and 8 provides the principal's objective function and the agent's constraint. Maximizing this objective function subject to this constraint yields equilibrium contractual terms $b_i^{**} = \gamma - (\alpha[1-\beta(1-\lambda)]^2/8)$ and $m_i^{**} = 1/2$, which implies an equilibrium effort level $e_i^{**} = \alpha[1-\beta(1-\lambda)]/2$, equilibrium expected payoffs $z_{Ai}^{**} = E[\Pi_{Ai}^{**}] = \gamma$ and $z_{Pi}^{**} = E[\Pi_{Pi}^{**}] = (3\alpha[1-\beta(1-\lambda)]^2/8) - \gamma$, and a principal's participation constraint $\gamma < 3\alpha[1-\beta(1-\lambda)]^2/8$.

Intermediation Scenario: Matching and Coordination Stages. Substituting z_{Pi}^{**} and z_{Ai}^{**} into the matching stage results yields $y_{Pi}^{**} = (3\alpha[1-\beta(1-\lambda)]^2 - 8\gamma)[1+\theta(1-\tau)+\tau]/16$ and $y_{Ai}^{**} = \gamma[1+\theta(1-\tau)+\tau]/2$. For the coordination stage, the platform's optimum value of g to maximize Equation 5 is $g^* = \delta - [\eta\rho(\omega-\mu)/2]$. Substituting $g^*, y_{Ai}^{**}, y_{Pi}^{**}, y_{Ad}^{**}$, and y_{Pd}^{**} into Equations 4 through 6 yields our equilibrium expected results for $E[U_{Pi}^{**}]$, $E[U_{Ai}^{**}]$, $E[U_{Ii}^{**}]$, and $E[U_{Wi}^{**}]$. The formulas for these results are complicated, so we show them in Appendix section I.

2.4.7 Propositions Without Privacy Concerns

In Appendix section I, we generate comparative statics results by differentiating each of the four equilibrium expected payoffs (i.e., $E[U_{Pi}^{**}]$ for the principal, $E[U_{Ai}^{**}]$ for the agent, $E[U_{Ii}^{**}]$ for the platform, and $E[U_{Wi}^{**}]$ for total welfare) with respect to the parameters representing the strengths of the platform's three capabilities for mitigating the informational problems underlying market frictions (i.e., δ for coordination problems, τ for search costs, and λ for transactional hazards). Specifically, in order to check for demand-side synergies across these three capabilities, we calculate cross-partial second derivatives with respect to all three possible pairs of these three parameters (i.e., δ and τ, δ and λ, τ and λ). With four outcome variables and three pairs of parameters, we therefore calculate a total of twelve comparative statics derivatives, ten of which are synergistic (i.e., unambiguously positive), with the remaining two being zero. So, we propose:

> ***Proposition 1a:*** *Without privacy concerns, the platform's coordination and matching functions are synergistic for the principal's expected payoff, for the agent's expected payoff, for the platform's expected profit, and for expected total welfare.*

> ***Proposition 1b:*** *Without privacy concerns, the platform's coordination and transaction de-hazarding functions are synergistic for the principal's expected payoff, for the platform's expected profit, and for expected total welfare.*

> ***Proposition 1c:*** *Without privacy concerns, the platform's matching and transaction de-hazarding functions are synergistic for the principal's expected payoff, for the platform's expected profit, and for expected total welfare.*

The economic interpretations for the propositions involving the matching function – i.e. Propositions 1a and 1c – are straightforward: In order to reap any benefit from coordinating (1a) or from transacting (1c), one must find a partner with whom to transact or coordinate. The platform's matching ability increases the probability of finding such a partner, and therefore increases the probability of experiencing the value created via coordination (1a) or via transacting (1c). The economic interpretation of Proposition 1b – synergy between coordinating and transacting – is that the parties cannot transact unless they have first adopted a common standard to coordinate. The platform's coordination ability increases the probability of agreeing to such a common standard. In propositions 1a and 1b, during a transaction function principal has no reason to compensate agent beyond his/her reservation expected utility, so principal captures all of the excess – serving in effect, as residual claimant of the transaction function. So, the agent experiences no synergies between transacting and either of the other two functions, coordinating (1b) or matching (1c).

2.5 Extended Model with Privacy Concerns

We now extend the baseline model from the previous section in order to investigate how incorporating privacy concerns affects the synergies between the three platform functions. We make only one change to our assumptions – in the intermediation scenario only, the agent suffers a cost or loss of utility in direct proportion to the platform's de-hazarding capability λ, since this capability specifically requires the platform to collect information about the agent and thereby invade (perhaps intrusively) the agent's privacy. We can think of this cost or utility reduction as arising from a number of different possible sources: It could be psychological in nature, due to uncomfortable (perhaps even irrational) feelings about being monitored by the platform. It may be due to ways that the platform uses the information it collects in ways that are contrary to the agent's perceived interests, such as using it for targeted marketing campaigns or selling the data to third parties. It might simply reflect the material cost or inconvenience of submitting information to the platform or being monitored. It can also capture the expected value of a possible future financial or material loss due to the prospect of a data breach that releases the platform's information either publicly or to hackers with nefarious intent. Or it could arise from some combination of these causes. In any case, we assume in this extended version of the model that the agent's payoff is $\Pi_{Ai\phi} = W_{i\phi} - c_{Ai\phi} - \phi\lambda$ in the intermediation scenario only, where the parameter $\phi > 0$ represents the severity or intensity of the agent's privacy concerns. We also use ϕ as a subscript to indicate variables that are from this privacy-focused extension of the model, and to differentiate them from the corresponding variables in the baseline model without privacy concerns. With the exception of this one term being added to the agent's payoff function, everything else about the extended version of the model is identical to the baseline model without privacy concerns.

2.5.1 Extended Model Solution Via Backward Induction

Since our only change in assumptions here pertains to the intermediation scenario, the disintermediation scenario remains completely unchanged from the baseline model. In the intermediation scenario, the equilibrium base compensation changes to $b_{i\phi}^{**} = \gamma + \phi\lambda - (\alpha[1-\beta(1-\lambda)]^2/8)$, which changes the principal's equilibrium expected payoffs to $z_{Pi\phi}^{**} = E[\Pi_{Pi\phi}^{**}] = (3\alpha[1-\beta(1-\lambda)]^2/8) - \gamma - \phi\lambda$ and participation constraint to $\gamma + \phi\lambda < 3\alpha[1-\beta(1-\lambda)]^2/8$. In this equilibrium, the principal fully absorbs the cost of compensating the agent to overcome the privacy concerns, so the agent's payoffs remain unchanged from the baseline model. However, the equilibrium expected results – i.e., $E[U_{Pi\phi}^{**}]$ for the principal, $E[U_{Ii\phi}^{**}]$ for the platform, and $E[U_{Wi\phi}^{**}]$ for total welfare – are changed, as shown in Appendix section II.

2.5.2 Propositions With Privacy Concerns

In Appendix section II, we generate comparative statics results by taking similar derivatives corresponding to the twelve that we had taken in the baseline model (Appendix section I). In contrast to the ten synergies shown in the baseline model's derivatives, which had been unbounded (i.e., present under all allowable parameter values satisfying our model assumptions), most of the synergies shown in the extended model's derivatives are bounded insofar as they can disappear, or even become reversed into counter-synergies, when the severity or intensity of the agent's privacy concerns (ϕ) gets sufficiently large. Only two of the ten synergies from the baseline model remain unbounded in the extended model – the synergies between coordination and matching capabilities (δ and τ) in the equilibrium expected payoffs of the principal and the agent. So, we propose:

> ***Proposition 2a:*** *With privacy concerns, the platform's coordination and matching functions are synergistic for the principal's payoff and the agent's payoff. They are also synergistic for the platform profit, and for social welfare up to a threshold level of privacy concerns, but beyond that threshold level they are counter-synergistic.*

Proposition 2b: *With privacy concerns, the platform's coordination and transaction de-hazarding functions are synergistic for the principal's expected payoff, for the platform's expected profit, and for expected total welfare up to a threshold level of privacy concerns, but beyond that threshold level they are counter-synergistic.*

Proposition 2c: *With privacy concerns, the platform's matching and transaction de-hazarding functions are synergistic for the principal's expected payoff, for the platform's expected profit, and for expected total welfare up to a threshold level of privacy concerns, but beyond that threshold level they are counter-synergistic.*

The economic interpretation of these propositions is straightforward: Concerns about invasion of privacy by the platform in the exercise of its transaction de-hazarding function naturally reduce the benefit that the platform can provide in that function. Since that transactional benefit can only be experienced by transacting parties who have already been matched with each other and have also already adopted a common standard for interacting with each other, the interaction effects with these other two platform functions are also reduced.

Finally, in the derivatives from Appendix section II, we observe that the threshold level of privacy concerns at which synergies disappear and become counter-synergistic is the same for two of the three synergies – namely, for the synergy between the coordination and de-hazarding capabilities (δ and λ) and the synergy between the de-hazarding and matching capabilities (λ and τ). However, this threshold level is different for the third synergy – namely, between the coordination and matching capabilities (δ and τ). Depending upon the strength of the platform's de-hazarding capability (λ), this third threshold may be either above or below the other two. Therefore, depending upon both the severity or intensity of the agent's privacy concerns (ϕ) and the strength of the platform's de-hazarding capability (λ), it is possible for one of the synergies to be positive while the other two are negative (i.e., counter-synergistic) or vice versa. Therefore, this difference between the threshold levels of the three synergies may be one factor (albeit only one factor) that can begin to help explain why different platforms lubricate different combinations of economic frictions, and why some platforms lubricate more frictions than others, as shown in the Venn diagram of Figure 2.3. Hence, we propose:

> ***Proposition 3:*** *The threshold level of privacy concerns above which the synergy between coordination and matching capabilities becomes counter-synergistic may be either higher or lower than the corresponding threshold for the other two synergies (between coordination and transaction de-hazarding capabilities, and between matching and transaction de-hazarding capabilities), depending upon the severity or intensity of the agent's privacy concerns and the strength of the platform's de-hazarding capability.*

2.6 Discussion and Conclusion

Our model offers a first step toward unpacking and understanding how this transition works from an economic perspective. Subtly embedded in the Isaacson quotation above are all three of the informational problems that we model, all three of the platform functions shown in the Venn diagram of Figure 2.3: The iPhone started as a pure coordination mechanism. Like any computer operating system, the iPhone's iOS serves the coordination function of defining the standard protocols by which application software programs (i.e., apps) interact with users and with each other. A programmer's failure to follow these coordination protocols may "create applications for the iPhone that could mess it up." At first, Apple could, by management fiat, ensure that its own programmers would follow those protocols correctly, but doing so for outside developers required that apps "be tested and approved by Apple." Yet such coordination alone was not enough, since iPhone users also faced the transactional hazard of apps that might "infect it with viruses, or pollute its integrity." So, third-party apps "would have to meet strict standards... and be sold only through the iTunes Store" where Apple could vouch for their quality, in order "to protect the integrity of the iPhone." Moreover, the exponentially rapid proliferation of iPhone apps required the App Store to include search functions to match users with the right apps in order to preserve "the simplicity of the customer experience" from the laborious challenge of browsing individually through each of the App Store's 2.2 million offerings. Moreover, the App Store's extraordinary success suggests that Apple created some fairly strong synergies between these three platform functions.

2.6.1 Summary of Contributions

By focusing on classic market-frictions logic from information economics, rather than information technology *per se*, this paper is intended to help re-frame research on platform business models, especially with regard to how they create and capture value. We argue that platforms solve three classic information-economics frictions – search costs, coordination costs, and transaction costs – in one or more combinations. The digital technology and mobile telecommunications revolutions have undoubtedly unleashed a variety of new possibilities in the scale and scope of platform business models, but the underlying strength of platforms lies in the synergies among the capabilities for solving these three longstanding informational problems, which preceded modern technology. While they enable synergies, privacy concerns in platform-based business models can limit their effectiveness and, in some circumstances, even reverse these synergies.

Whether specific platforms manage this value creation and capture process effectively is more of an empirical inquiry, as is the question of how platforms come to one approach of platform governance compared to the other. However, the road map provided in this paper demonstrates that the necessary condition to build any viable platform-based business starts with their ability to solve one or more market frictions effectively. In this paper, we provide a needed corrective to the current platform literature, which often focuses on superficial stylistic differences and unique aspects of the seemingly distinctive platform phenomenon, such as network effects, enabling users with reviews and ratings, orchestration of complementors, and alignment of actors. Although these new organizational forms undoubtedly have unconventional characteristics, we argue that they can nevertheless be better understood through the lens of corporate strategy theory. In terms of understanding how platforms lubricate market frictions, this lens has been under-utilized, leading to some "wheels" being reinvented and some "old wine" being re-bottled in the current literature on platform businesses, thereby falling short of the goal for high-quality research to be cumulative in nature (Oxley *et al.*, 2010). By focusing on synergies among a platform's informational functions, this paper aims to provide a first step toward understanding platform design as arising from classic corporate strategy logic.

We also respond to the call in the field to expand RBT research into new forms of digitally intermediated platforms. We provide a perspective on how platforms build their competencies and business models by creating synergies through combinations of resources and capabilities. By clarifying the map for value creation and value capture, we offer an explanation for how resources (or lack thereof) facilitate (or limit) the extent of synergies (or counter-synergies) in the interactions among several market players, which may provide the basis for a competitive advantage.

Finally, we also contribute to the burgeoning interdisciplinary platform literature. Since digital platforms are organized for market players with loose contractual connections to solve information problems together, it is important to understand what type of corporate strategies facilitate optimal resource configuration and incentive structures. Our paper initiates conversation with platform researchers about carefully examining: (1) What are the corporate strategy aspects of platform-based business models that are consistent with what we know about other businesses? (2) What are the corporate strategy aspects of platform-based business models that are different from what we know about other businesses? (3) As researchers, what can we do about it?

2.6.2 Caveats, Limitations, and Implications for Future Research

This study has several limitations due to choices we made for tractability of the formal model and therefore leaves open several opportunities for future research. For example, we limit our model to a two-sided market with an asymmetric unidirectional agency relationship between the two sides. In this regard, it is probably most directly relevant for business-to-consumer (B2C) types of platforms. Future extensions of the model could broaden it to be more applicable for consumer-to-consumer (C2C), business-to-business (B2B), or peer-to-peer (P2P) types of platforms by allowing for (1) multi-sided markets and (2) a more bidirectional agency relationship between the two sides (e.g., dating platforms).

Also, in this paper, we limit our focus on the scope decisions within the platform, while implicitly holding the scaling effect constant. This implicit *ceteris paribus* assumption may not be valid, since a platform's three informational functions may differ widely both in their scalability and in how effectively they contribute to direct and indirect network effects. Therefore, future extensions of our model that explicitly incorporate scaling mechanisms, including direct and indirect network effects, may help capture some interesting additional features observed in platform business models.

2.7 REFERENCES

Adner R. 2017. Ecosystem as Structure: An Actionable Construct for Strategy. *Journal of Management* **43**(1): 39-58.

Adner R, Kapoor R. 2010. Value Creation in Innovation Ecosystems: How the Structure of Technological Interdependence Affects Firm Performance in New Technology Generations. *Strategic Management journal* **31**(3): 306-333.

Ahuja G, Novelli E. 2017. Redirecting Research Efforts on the Diversification–Performance Linkage: The Search for Synergy. *Academy of Management Annals* **11**(1): 342-390.

Akerlof GA. 1970. The Market for 'Lemons': Qualitative Uncertainty and the Market Mechanism. *Quarterly Journal of Economics* **84**: 488-500.

Anderson C, Andersson MP. 2004. Long Tail.

Athey S, Calvano E, Gans J. 2013. The Impact of the Internet on Advertising Markets for News Media: National Bureau of Economic Research.

Aumann RJ. 1974. Subjectivity and Correlation in Randomized Strategies. *Journal of Mathematical Economics* **1**(1): 67-96.

Aumann RJ. 1987. Correlated Equilibrium as an Expression of Bayesian Rationality. *Econometrica* **55**(1): 1-18.

Barney JB. 1991. Firm Resources and Sustained Competitive Advantage. *Journal of Management* **17**(1): 99-120.

Bel R. 2018. A Property Rights Theory of Competitive Advantage. *Strategic Management Journal* **39**(6): 1678-1703.

Boudreau K. 2010. Open Platform Strategies and Innovation: Granting Access Vs. Devolving Control. *Management Science* **56**(10): 1849-1872.

Boudreau K. 2012. Let a Thousand Flowers Bloom? An Early Look at Large Numbers of Software App Developers and Patterns of Innovation. *Organization Science* **23**(5): 1409-1427.

Boudreau K. 2017. Platform Boundary Choices & Governance: Opening-up While Still Coordinating and Orchestrating☆. In *Entrepreneurship, Innovation, and Platforms.* Emerald Publishing Limited.

Brynjolfsson E, Hu YJ, Smith M. 2006. From Niches to Riches: Anatomy of the Long Tail. *Sloan Management Review* **47**(4): 67-71.

Brynjolfsson E, Kahin B. 2002. *Understanding the Digital Economy: Data, Tools, and Research*. MIT press.

Chatain O. 2011. Value Creation, Competition, and Performance in Buyer-Supplier Relationships. *Strategic Management Journal* **32**(1): 76-102.

Cooper R. 1999. *Coordination Games*. Cambridge University Press.

Dawson A, Hirt M, Scanlan J. 2016. The Economic Essentials of Digital Strategy. *McKinsey Quarterly* **3**: 45.

Diamond PA. 1971. A Model of Price Adjustment. *Journal of Economic Theory* **3**(2): 156-168.

Einav L, Farronato C, Levin J. 2016. Peer-to-Peer Markets. *Annual Review of Economics* **8**: 615-635.

Eisenmann T, Parker G, Van Alstyne M. 2011. Platform Envelopment. *Strategic Management Journal* **32**(12): 1270-1285.

Ellison G, Ellison S. 2005. Lessons About Markets from the Internet. *Journal of Economic Perspectives* **19**(2): 139-158.

Feldman E. 2019. Corporate Strategy: Past, Present and Future. *Strategic Management Review*.

Fisman R, Sullivan T. 2016. *The Inner Lives of Markets : How People Shape Them--and They Shape Us*.

Forman C, Ghose A, Wiesenfeld B. 2008. Examining the Relationship between Reviews and Sales: The Role of Reviewer Identity Disclosure in Electronic Markets. *Information Systems Research* **19**(3): 291-313.

Fradkin A. 2017. Digital Marketplaces, Website: http://andreyfradkin.com/assets/econ_of_digital.pdf.

Ghazawneh A, Henfridsson O. 2015. A Paradigmatic Analysis of Digital Application Marketplaces. *Journal of Information Technology* **30**(3): 198-208.

Goldfarb A, Tucker C. 2011. Online Display Advertising: Targeting and Obtrusiveness. *Marketing Science* **30**(3): 389-404.

Goldfarb A, Tucker C. 2019. Digital Economics. *Journal of Economic Literature* **57**(1): 3-43.

Grossman S, Hart O. 1983. An Analysis of the Principal-Agent Problem. *Econometrica* **52**: 1-45.

Hagiu A, Wright J. 2015. Multi-Sided Platforms. *International Journal of Industrial Organization* **43**: 162-174.

Hannah DP, Eisenhardt KM. 2018. How Firms Navigate Cooperation and Competition in Nascent Ecosystems. *Strategic Management Journal* **39**(12): 3163-3192.

Helfat C, Eisenhardt K. 2004. Inter-Temporal Economies of Scope, Organizational Modularity, and the Dynamics of Diversification. *Strategic Management Journal* **25**(13): 1217-1232.

Helfat CE, Peteraf MA. 2003. The Dynamic Resource-Based View: Capability Lifecycles. *Strategic Management Journal* **24**(10): 997-1010.

Hinterhuber A. 2002. Value Chain Orchestration in Action and the Case of the Global Agrochemical Industry. *Long Range Planning* **35**(6): 615-635.

Hosanagar K, Fleder D, Lee D, Buja A. 2013. Will the Global Village Fracture into Tribes? Recommender Systems and Their Effects on Consumer Fragmentation. *Management Science* **60**(4): 805-823.

Isaacson W. 2011. *Steve Jobs*. Simon & Schuster: New York.

Jacobides MG, Cennamo C, Gawer A. 2018. Towards a Theory of Ecosystems. *Strategic Management Journal* **39**(8): 2255-2276.

Karim S, Kaul A. 2014. Structural Recombination and Innovation: Unlocking Intraorganizational Knowledge Synergy through Structural Change. *Organization Science* **26**(2): 439-455.

Klemperer P, Padilla AJ. 1997. Do Firms' Product Lines Include Too Many Varieties? *The RAND Journal of Economics* **28**(3): 472-488.

Lemelin A. 1982. Relatedness in the Patterns of Interindustry Diversification. *Review of Economics and Statistics* **64**: 646-657.

Levinthal DA, Wu B. 2010. Opportunity Costs and Non-Scale Free Capabilities: Profit Maximization, Corporate Scope, and Profit Margins. *Strategic Management Journal* **31**(7): 780-801.

Mahoney J. 2001. A Resource-Based Theory of Sustainable Rents. *Journal of Management* **27**(6): 651-660.

Mahoney JT, Qian L. 2013. Market Frictions as Building Blocks of an Organizational Economics Approach to Strategic Management. *Strategic Management Journal* **34**(9): 1019-1041.

McIntyre DP, Srinivasan A. 2017. Networks, Platforms, and Strategy: Emerging Views and Next Steps. *Strategic Management Journal* **38**(1): 141-160.

Montgomery CA. 1994. Corporate Diversificaton. *Journal of Economic Perspectives* **8**(3): 163-178.

Nayyar PR. 1990. Information Asymmetries: A Source of Competitive Advantage for Diversified Service Firms. *Strategic Management Journal* **11**(7): 513-519.

Nayyar PR. 1993. Performance Effects of Information Asymmetry and Economies of Scope in Diversified Service Firms. *The Academy of Management Journal* **36**(1): 28-57.

Noe T, Parker G. 2005. Winner Take All: Competition, Strategy, and the Structure of Returns in the Internet Economy. *Journal of Economics & Management Strategy* **14**(1): 141-164.

Oliver J. 2014. Last Week Tonight with John Oliver. https://www.youtube.com/watch?v=fpbOEoRrHyU (9-12 2019).

Oxley JE, Rivkin JW, Ryall MD. 2010. The Strategy Research Initiative: Recognizing and Encouraging High-Quality Research in Strategy. *Strategic Organization* **8**(4): 377-386.

Panzar JC, Willig RD. 1981. Economies of Scope. *American Economic Review* **71**(2): 268-272.

Parker GG, Van Alstyne MW. 2005. Two-Sided Network Effects: A Theory of Information Product Design. *Management Science* **51**(10): 1494-1504.

Rochet J-C, Tirole J. 2003. Platform Competition in Two-Sided Markets. *Journal of the European Economic Association* **1**(4): 990-1029.

Roth AE, Sotomayor M. 1992. Two-Sided Matching. *Handbook of game theory with economic applications* **1**: 485-541.

Rothschild M, Stiglitz JE. 1976. Equilibrium in Competitive Insurance Markets: An Essay on the Economics of Imperfect Information. *Quarterly Journal of Economics* **90**(4): 630-649.

Sakhartov A, Folta T. 2014. Resource Relatedness, Redeployability, and Firm Value. *Strategic Management Journal* **35**(12): 1781-1797.

Sakhartov A, Folta T. 2015. Getting Beyond Relatedness as a Driver of Corporate Value. *Strategic Management Journal* **36**(13): 1939-1959.

Schmalensee R, Evans D. 2001. Some Economic Aspects of Antitrust Analysis in Dynamically Competitive Industries. *NBER Working Paper*(w8268).

Shapiro C, Varian HR. 1998. *Information Rules: A Strategic Guide to the Network Economy*. Harvard Business Press.

Spence AM. 1973. Job Market Signaling. *Quarterly Journal of Economics* **87**(3): 355-374.

Stigler GJ. 1961. The Economics of Information. *Journal of Political Economy* **69**(3): 213-225.

Stremersch S, Tellis GJ. 2002. Strategic Bundling of Products and Prices: A New Synthesis for Marketing. *Journal of Marketing* **66**(1): 55-72.

Teece D. 1980. Economies of Scope and the Scope of the Enterprise. *Journal of Economic Behavior and Organization* **1**: 223-247.

Teece D, Rumelt R, Dosi G, Winter S. 1994. Understanding Corporate Coherence: Theory and Evidence. *Journal of Economic Behavior & Organization* **23**(1): 1-30.

Tiwana A, Konsynski B, Bush AA. 2010. Research Commentary—Platform Evolution: Coevolution of Platform Architecture, Governance, and Environmental Dynamics. *Information Systems Research* **21**(4): 675-687.

Wernerfelt B. 1984. A Resource-Based View of the Firm. *Strategic Management Journal* **5**(2): 171-180.

Zhou YM. 2011. Synergy, Coordination Costs, and Diversification Choices. *Strategic Management Journal* **32**(6): 624-639.

Zhu F, Furr N. 2016. Products to Platforms: Making the Leap. *Harv. Bus. Rev.* **94**(4): 72-78.

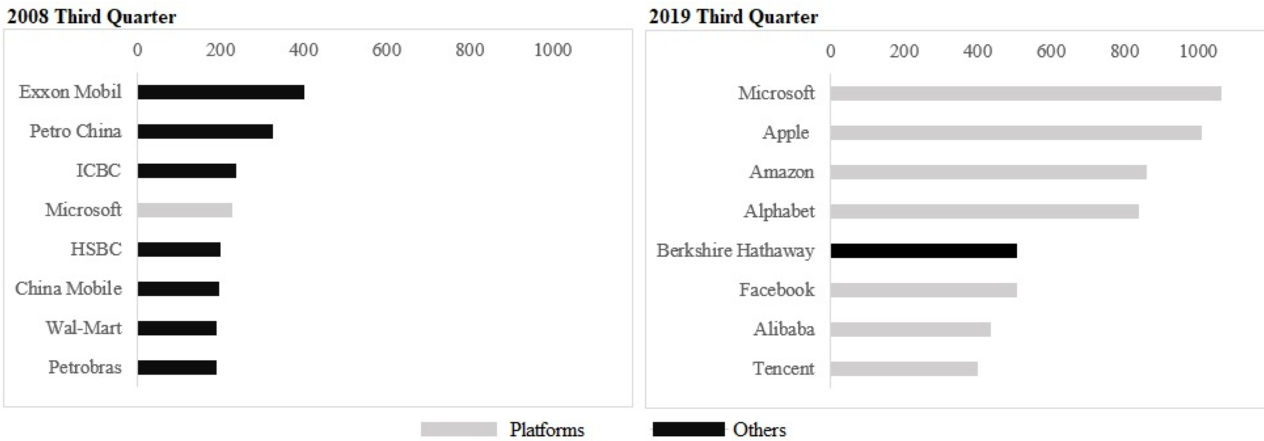

Figure 2.1 World's Largest Publicly Traded Companies by Market Cap (US $ Billions)

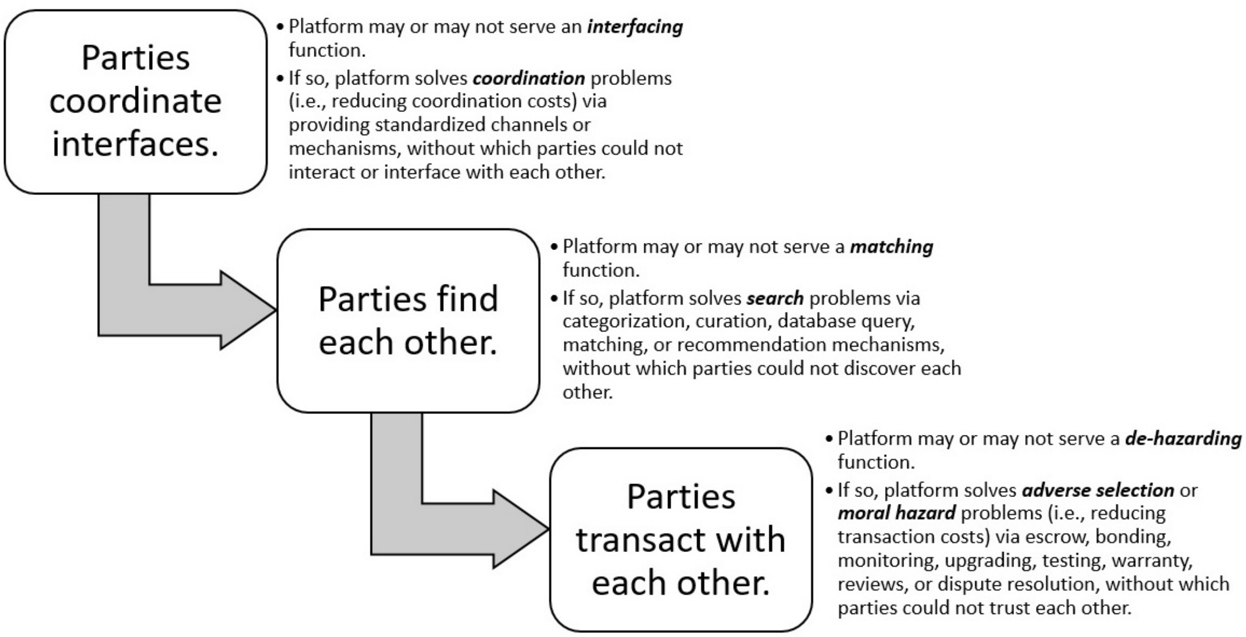

Figure 2.2. Platform Functions

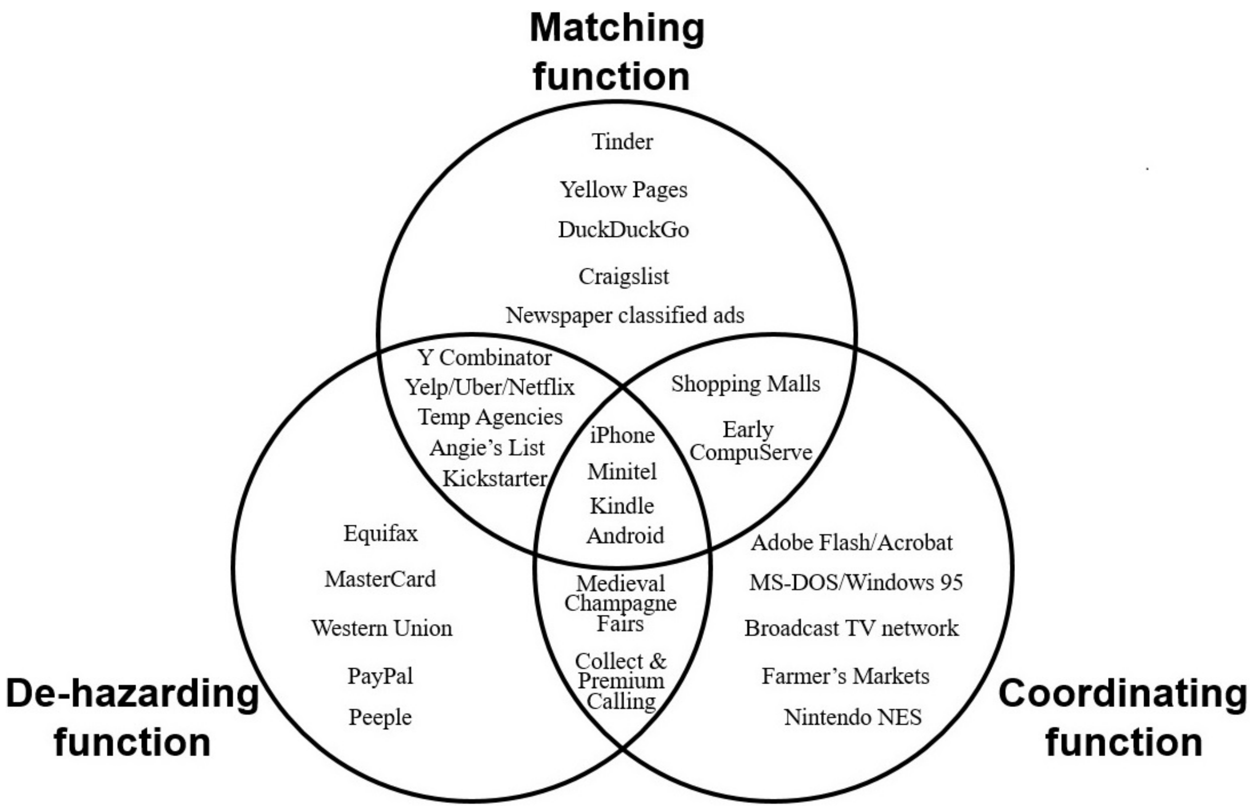

Figure 2.3. Examples of Platforms Performing Different Combinations of Functions

Table 2.1.Coordination Game Payoffs of a Typical Representative Principal/Agent Pair (P, A)

		Agent (A)	
		Not Accommodate (n)	Accommodate (a)
Principal (P)	Not Accommodate (n)	$(0, 0)$	$(y_P + \omega, y_A - \mu)$
	Accommodate (a)	$(y_P - \mu, y_A + \omega)$	$(y_P + \omega - \mu, y_A + \omega - \mu)$

APPENDIX 2A

I. Equilibrium Expected Results and Comparative Statics Without Privacy Concerns

$$E[U_{Pi}^{**}] = \frac{1}{16}(8(\frac{3}{8}\alpha(-1+\beta)^2-\gamma)(1+\theta)\rho+(8\gamma-3\alpha\big(1+\beta(-1+\lambda)\big)^2)(\delta-\delta\rho)(-1+\theta(-1+\tau)-\tau)-8\rho(2+\eta(-1+\rho)(\mu-\omega))(\mu-\omega)-\frac{256\mu\rho\omega}{(3\alpha(-1+\beta)^2-8\gamma)(1+\theta)})$$

(A1)

$$E[U_{Ai}^{**}] = \frac{1}{2}(\gamma(1+\theta)\rho+\delta\gamma(1-\rho)(1+\theta+\tau-\theta\tau)+\rho(2+\eta(1-\rho)(\omega-\mu))(\omega-\mu)-\frac{4\mu\rho\omega}{\gamma+\gamma\theta})$$

(A2)

$$E[U_{Ii}^{**}] = \frac{1}{2}\rho(-(\frac{3}{8}\alpha(1-\beta)^2-\gamma)(1+\theta)-\gamma(1+\theta)+2\delta(\frac{1}{16}(8\gamma-3\alpha\big(1+\beta(-1+\lambda)\big)^2)(-1+\theta(-1+\tau)-\tau)+\frac{1}{2}\gamma(1+\theta+\tau-\theta\tau))+(4+\eta\rho(\mu-\omega))(\mu-\omega)+\frac{4\mu\omega}{(\frac{3}{8}\alpha(-1+\beta)^2-\gamma)(1+\theta)}+\frac{4\mu\omega}{\gamma(1+\theta)})$$

(A3)

$$E[U_{Wi}^{**}] = \frac{1}{16}(\delta(8\gamma-3\alpha\big(1+\beta(-1+\lambda)\big)^2)(-1+\theta(-1+\tau)-\tau)+8\gamma\delta(1+\theta+\tau-\theta\tau)-8\eta(-2+\rho)\rho(\mu-\omega)^2)$$

(A4)

$$\frac{\partial E[U_{Pi}^{**}]}{\partial\delta\,\partial\lambda} = (1-\rho)[1+\theta(1-\tau)+\tau]\left(\frac{3\alpha\beta[1-\beta(1-\lambda)]}{8}\right) > 0 \tag{A5}$$

$$\frac{\partial E[U_{Pi}^{**}]}{\partial\delta\,\partial\tau} = (1-\rho)(1-\theta)\left(\frac{3\alpha[1-\beta(1-\lambda)]^2-8\gamma}{16}\right) > 0 \tag{A6}$$

$$\frac{\partial E[U_{Pi}^{**}]}{\partial\lambda\,\partial\tau} = (1-\rho)(1-\theta)\left(\frac{3\alpha\beta\delta[1-\beta(1-\lambda)]}{8}\right) > 0 \tag{A7}$$

$$\frac{\partial E[U_{Ai}^{**}]}{\partial\delta\,\partial\lambda} = 0 \tag{A8}$$

$$\frac{\partial E[U_{Ai}^{**}]}{\partial\delta\,\partial\tau} = \frac{\gamma}{2}(1-\rho)(1-\theta) > 0 \tag{A9}$$

$$\frac{\partial E[U_{Ai}^{**}]}{\partial\lambda\,\partial\tau} = 0 \tag{A10}$$

$$\frac{\partial E[U_{Ii}^{**}]}{\partial\delta\,\partial\lambda} = [1+\theta(1-\tau)+\tau]\left(\frac{3\alpha\beta\rho[1-\beta(1-\lambda)]}{8}\right) > 0 \tag{A11}$$

$$\frac{\partial E[U_{Ii}^{**}]}{\partial\delta\,\partial\tau} = (1-\theta)\left(\frac{3\alpha\rho[1-\beta(1-\lambda)]^2}{16}\right) > 0 \tag{A12}$$

$$\frac{\partial E[U_{Ii}^{**}]}{\partial\lambda\,\partial\tau} = (1-\theta)\left(\frac{3\alpha\beta\delta\rho[1-\beta(1-\lambda)]}{8}\right) > 0 \tag{A13}$$

$$\frac{\partial E[U_{Wi}^{**}]}{\partial \delta\, \partial \lambda} = [1 + \theta(1-\tau) + \tau]\left(\frac{3\alpha\beta[1-\beta(1-\lambda)]}{8}\right) > 0 \quad \text{(A14)}$$

$$\frac{\partial E[U_{Wi}^{**}]}{\partial \delta\, \partial \tau} = (1-\theta)\left(\frac{3\alpha[1-\beta(1-\lambda)]^2}{16}\right) > 0 \quad \text{(A15)}$$

$$\frac{\partial E[U_{Wi}^{**}]}{\partial \lambda\, \partial \tau} = (1-\theta)\left(\frac{3\alpha\beta\delta[1-\beta(1-\lambda)]}{8}\right) > 0 \quad \text{(A16)}$$

II. Equilibrium Expected Results and Comparative Statics With Privacy Concerns

$$E[U_{Pi\phi}^{**}] = \frac{1}{16}(8(\tfrac{3}{8}\alpha(-1+\beta)^2 - \gamma)(1+\theta)\rho + (\delta - \delta\rho)(-1+\theta(-1+\tau)-\tau)(-3\alpha\left(1+\beta(-1+\lambda)\right)^2 + 8(\gamma+\lambda\phi)) - 8\rho(2+\eta(-1+\rho)(\mu-\omega))(\mu-\omega) - \frac{256\mu\rho\omega}{(3\alpha(-1+\beta)^2-8\gamma)(1+\theta)})$$
(A17)

$$E[U_{Ai}^{**}] = \frac{1}{2}(\gamma(1+\theta)\rho + \delta\gamma(1-\rho)(1+\theta+\tau-\theta\tau) + \rho(2+\eta(1-\rho)(\omega-\mu))(\omega-\mu) - \frac{4\mu\rho\omega}{\gamma+\gamma\theta})$$
(A18)

$$E\left[U_{Ii\phi}^{**}\right] = \frac{1}{2}\rho(-(\tfrac{3}{8}\alpha(-1+\beta)^2-\gamma)(1+\theta) - \gamma(1+\theta) + 2\delta(\tfrac{1}{2}\gamma(1+\theta+\tau-\theta\tau) + \frac{1}{16}(-1+\theta(-1+\tau)-\tau)(-3\alpha\left(1+\beta(-1+\lambda)\right)^2 + 8(\gamma+\lambda\phi))) + (4+\eta\rho(\mu-\omega))(\mu-\omega) + \frac{4\mu\omega}{(\frac{3}{8}\alpha(-1+\beta)^2-\gamma)(1+\theta)} + \frac{4\mu\omega}{\gamma(1+\theta)})$$
(A19)

$$E\left[U_{Wi\phi}^{**}\right] = \frac{1}{16}(8\gamma\delta(1+\theta+\tau-\theta\tau) + \delta(-1+\theta(-1+\tau)-\tau)(-3\alpha\left(1+\beta(-1+\lambda)\right)^2 + 8(\gamma+\lambda\phi)) - 8\eta(-2+\rho)\rho(\mu-\omega)^2)$$
(A20)

$$\frac{\partial E[U_{Pi\phi}^{**}]}{\partial \delta\, \partial \lambda} = (1-\rho)[1+\theta(1-\tau)+\tau]\left(\frac{3\alpha\beta[1-\beta(1-\lambda)]-4\phi}{8}\right) > 0 \quad \text{iff} \quad \phi < \frac{3\alpha\beta[1-\beta(1-\lambda)]}{4} \quad \text{(A21)}$$

$$\frac{\partial E[U_{Pi\phi}^{**}]}{\partial \delta\, \partial \tau} = (1-\rho)(1-\theta)\left(\frac{3\alpha[1-\beta(1-\lambda)]^2-8(\gamma+\lambda\phi)}{16}\right) > 0 \quad \text{(A22)}$$

$$\frac{\partial E[U_{Pi\phi}^{**}]}{\partial \lambda\, \partial \tau} = (1-\rho)(1-\theta)\left(\frac{3\alpha\beta\delta[1-\beta(1-\lambda)]-4\phi}{8}\right) > 0 \quad \text{iff} \quad \phi < \frac{3\alpha\beta[1-\beta(1-\lambda)]}{4} \quad \text{(A23)}$$

$$\frac{\partial E[U_{Ai\phi}^{**}]}{\partial \delta\, \partial \lambda} = 0 \quad \text{(A24)}$$

$$\frac{\partial E[U_{Ai\phi}^{**}]}{\partial \delta\, \partial \tau} = \frac{\gamma}{2}(1-\rho)(1-\theta) > 0 \quad \text{(A25)}$$

$$\frac{\partial E[U_{Ai\phi}^{**}]}{\partial \lambda\, \partial \tau} = 0 \quad \text{(A26)}$$

$$\frac{\partial E[U_{Ii\phi}^{**}]}{\partial \delta\, \partial \lambda} = \rho[1+\theta(1-\tau)+\tau]\left(\frac{3\alpha\beta[1-\beta(1-\lambda)]-4\phi}{8}\right) > 0 \quad \text{iff} \quad \phi < \frac{3\alpha\beta[1-\beta(1-\lambda)]}{4} \quad \text{(A27)}$$

$$\frac{\partial E[U_{Ii\phi}^{**}]}{\partial\delta\,\partial\tau} = \rho(1-\theta)\left(\frac{3\alpha[1-\beta(1-\lambda)]^2-8\lambda\phi}{16}\right) > 0 \quad \text{iff} \quad \phi < \frac{3\alpha[1-\beta(1-\lambda)]^2}{8\lambda} \tag{A28}$$

$$\frac{\partial E[U_{Ii\phi}^{**}]}{\partial\lambda\,\partial\tau} = \rho\delta(1-\theta)\left(\frac{3\alpha\beta[1-\beta(1-\lambda)]-4\phi}{8}\right) > 0 \quad \text{iff} \quad \phi < \frac{3\alpha\beta[1-\beta(1-\lambda)]}{4} \tag{A29}$$

$$\frac{\partial E[U_{Wi\phi}^{**}]}{\partial\delta\,\partial\lambda} = [1+\theta(1-\tau)+\tau]\left(\frac{3\alpha\beta[1-\beta(1-\lambda)]-4\phi}{8}\right) > 0 \quad \text{iff} \quad \phi < \frac{3\alpha\beta[1-\beta(1-\lambda)]}{4} \tag{A30}$$

$$\frac{\partial E[U_{Wi\phi}^{**}]}{\partial\delta\,\partial\tau} = (1-\theta)\left(\frac{3\alpha[1-\beta(1-\lambda)]^2-8\lambda\phi}{16}\right) > 0 \quad \text{iff} \quad \phi < \frac{3\alpha[1-\beta(1-\lambda)]^2}{8\lambda} \tag{A31}$$

$$\frac{\partial E[U_{Wi\phi}^{**}]}{\partial\lambda\,\partial\tau} = \delta(1-\theta)\left(\frac{3\alpha\beta[1-\beta(1-\lambda)]-4\phi}{8}\right) > 0 \quad \text{iff} \quad \phi < \frac{3\alpha\beta[1-\beta(1-\lambda)]}{4} \tag{A32}$$

CHAPTER 4. DECISION RIGHT ALLOCATION AND PLATFORM MARKET EFFECTIVENESS:

4.1 Introduction

Often organized as a two-sided market, platforms aim to align participating complementors towards a core value proportion (Adner, 2017; Baldwin & Woodard, 2009; McIntyre & Srinivasan, 2017). While complementors' participation in value creation activities on the platform is critical to platform success (Rochet & Tirole, 2003; Wareham, Fox, & Giner, 2014; Zhu & Liu, 2018), creating an "alignment structure" (Adner, 2017, p. 40) to attract participation by the "right" kind of complementors (Boudreau & Hagiu, 2009, p. 184) presents a major information-related challenge to the platform owner. Despite complementors on different sides of the platform having heterogeneous backgrounds and information sets (Lanzolla & Frankort, 2016; McIntyre & Srinivasan, 2017), the platform owner needs to facilitate economic exchanges to happen between them directly (Evans & Schmalensee, 2016).

A growing stream of research seeks to understand the ways the platform owner tackles this challenge and reduces information asymmetries surrounding economic exchanges between complementors (e.g., Evans & Schmalensee, 2016; Einav et al., 2018). For instance, scholars in different fields ranging from economics to marketing to MIS have shown that feedback systems (e.g., ratings, reviews), customer satisfaction assurance programs (e.g., free return policies), and signaling mechanisms (e.g., Chevalier & Mayzlin, 2006; Hosanagar et al., 2013; Jin & Kato, 2007) can help mitigate the effects of information asymmetry and facilitate the efficient functioning of platform markets. Although these studies have significantly improved our existing knowledge, little research has examined how platform owners can leverage governance mechanisms—a topic core to strategy scholars—to alleviate problems of information asymmetry and enhance platform market effectiveness.

This paper focuses on one important governance mechanism available to platform owners—the allocation of key decision rights—and its implications for information asymmetry and platform market effectiveness. A decision right refers to the right to make specific decisions and take actions (Jensen & Meckling, 1992; Williamson, 1975). Research on optimal rules of decision right allocation maintains that decision rights be allocated to the party with the "right" incentives and best information (Athey & Roberts, 2001; Jensen & Meckling, 1992). However, incentives and information do not always colocate with the same party. In such situations, Athey and Roberts (2001, p. 200) suggest "providing incentives to those with the best information so that they make the right decisions," or if not impossible or overly costly, transferring the needed information to those with the incentives for decision making.

To date, a large number of strategy and organization studies have investigated how decision rights are allocated (Arruñada et al., 2001; Ozmel et al., 2017; Tong & Li, 2013), and how decision right allocation is related to corporate strategy and performance (Argyres & Silverman, 2004; Foss et al., 2011; Vázquez, 2004), within firms as well as in interfirm relationships. By contrast, we know much less about how changes in the allocation of decision rights may matter to organizational performance, especially in the emerging context of platforms. This question is particularly important to understand because platform owners, unlike traditional firms, often do not form a full-blown contractual relationship with complementors. Most complementors are not salaried employees or traditional suppliers, and conventional means such as hierarchical or process control are less applicable in addressing the problem of information asymmetry (Liebeskind, 1996).

Therefore, the allocation of key decision rights between the platform and complementors has been highlighted as an important mechanism platform owners may rely on to orchestrate complementors' participation in value creation activities on the platform (Tiwana, Konsynski, & Bush, 2010).

Linking classic corporate strategy research on decision right allocation with emerging work on platform organizations, we argue that platform owners play a critical governance role in orchestrating the relationship between platform participants. Specifically, platform owners can leverage decision right allocation as a governance mechanism to mitigate problems of information asymmetry pervasive in platform markets, thus increasing platform effectiveness. Building on this insight, we predict that to the extent that the allocation of key decision rights is aligned with the distribution of information and incentives among participants in online platform businesses, platform effectiveness will be enhanced. We further predict that this effect due to decision right allocation will be stronger when greater relevant information is available offline in local environments.

We employ a quasi-experimental design to empirically examine our predictions by focusing on loan listings on Prosper Marketplace and LendingClub, two leading online peer-to-peer (P2P) lending platforms in the U.S. We exploit Prosper's sudden governance policy change in December 2010 reallocating the pricing right (right to set loan interest rates) from the complementors (lenders) to the platform (Prosper) itself, and compare the rate of loan requests being funded by lenders (funding rate) on Prosper with that on LendingClub, which did not experience such change and had retained the pricing right to itself since its inception. Difference-in-differences regression results show a significant increase in the funding rate of loan listings on Prosper after the policy change, using LendingClub as a benchmark and controlling for a large number of factors. Further, we find that this increase is larger, the larger the number of financial institutions in local areas that provide greater financial information.

Our study makes contributions to several strands of literature. First, we link emerging research on platform business with classic corporate strategy research on the allocation of decision rights, two important streams of work that have hitherto developed separately despite the close connection between them. We maintain that platform governance lies at the nexus of these two streams (Baldwin & Woodward, 2009; Tiwana et al., 2010), and we demonstrate that platform owners play a key governance or regulating role (Chu & Wu, 2019), emphasizing that decision right allocation can be used as a tool to mitigate information asymmetry and shape platform effectiveness. In our view, the governance perspective proposed and our focus on platforms represent a useful addition to an established body of literature on how asymmetric information affects governance choices in interfirm relationships and how governance choices in turn affect organizational and transactional efficiencies (see Reuer (2009) for a review of the literature). Second, our study moves beyond existing research on decision right allocation that often focused on the antecedents of the hierarchical or contractual allocation of decision rights within firms and in interfirm relationships in two ways (Argyres & Silverman, 2004; Arruñada et al., 2001; Foss et al., 2011; Vázquez, 2004): We extend the intellectual inquiry to a new yet increasingly-relevant mode of economic organization—platforms, and we show causal effects of how *changes* in decision right allocation may change market effectiveness using a quasi-experimental design. Third, our study adds to a growing body of research highlighting the importance of considering the interdependencies between online and offline information environments (Forman, Ghose, & Goldfarb, 2009; Lanzolla & Frankort, 2016) in designing digital platforms (Teece & Linden, 2017).

In particular, allocation of decision rights in online platform markets should be evaluated in line with attributes of the physical environment in which participants are embedded.

4.2 Theoretical Background

Platform governance concerns how the platform owner designs and deploys governance instruments, including decision rights, ownership structures, and control mechanisms, to shape the incentives and participation of the complementors (Adner, 2017; Boudreau & Hagiu, 2009; Tiwana et al., 2010). The *raison d'etre* for platform governance can be seen as aligning all actors on the platform—the platform owner and complementors—to realize a core value proposition (Adner, 2017). Unlike traditional organizations where the relationship among actors (e.g., the divisions in a multi-divisional firm) is more well-defined and subject to fiat, complementors often only have a loose, semi-autonomous relationship with the platform. A small but fast growing stream of strategy research has revealed valuable insights into how platform governance choices can shape complementors' incentives and their participation in platform activities. For example, Kretschmer and Claussen (2016) show that a new gaming console's backward compatibility, which can be seen as a "hard" regulation, negatively affects game developers' incentives in publishing new game titles. In addition, "soft" incentive structures and the timing of their deployment (Claussen et al., 2013) can also "nudge" app developers' incentives in creating software applications.

Among the various platform governance mechanisms, allocation of decision rights occupies a prominent position in the literature. Tiwana et al. (2010, p. 679) consider "decision right partitioning"—defined as "how decision-making authority is divided up between the platform owner and module developers (complementors)"—a core component of platform governance design. This perspective is also shared by other scholars who view platforms as a new mode of economic organization (Baldwin & Woodward, 2009; Boudreau, 2017). Division of decision rights then proves critical to the effective operation of platform organizations. In particular, it is suggested that appropriate allocation of key decision rights can help attract the "right" kind of participants to the platform (Boudreau & Hagiu, 2009), and give participants the incentive to contribute value creation activities.

On a general level, decision rights should be allocated in a way to avoid scenarios "in which important decision agents do not bear a substantial share of the wealth effects of their decisions" (Fama & Jensen, 1983, p. 301). Recent research on optimal rules of decision right allocation further argues that the colocation of information and decision authority improves organizational efficiency by aligning information with incentives (e.g., Athey & Roberts, 2001; Gibbons et al., 2013). Extending the ideas to the platform context, allocation of a decision right between the platform owner and the complementors must therefore consider whether the decision maker possesses both the information and incentives. Specifically, the platform owner would need to consider whether the information required for making the decision is with the party with the incentives, and if not, evaluate the cost of transferring information to the party so that she has the requisite information for decision making.

This basic idea can be illustrated by the different ways Airbnb and Uber allocate a key decision right—the right to set price—between the platform owner and the complementors. As is well known, Airbnb gives property owners (complementors) the right to set listing price as they have high-quality information about their properties, which are often idiosyncratic, and can make pricing decisions more efficiently than the platform (Zhu & Iansiti, 2019). By contrast, Uber retains to itself the right to price rides, which is deemed efficient as it has a huge informational advantage over drivers or riders in terms of the supply and demand conditions in real time, made possible through big data analytics (Cramer & Krueger, 2016). Thus, it can be said that even if a platform owner may want to allocate a decision right to the complementors, it may not be in the complementors' best interest if the platform, rather the complementors, has superior information. These examples also suggest that which agent (platform owner or complementors) has superior information for decision making can vary significantly from one platform to another, which leads to a discussion of our research context of P2P lending platforms below.

4.3 Online Peer-to-Peer Lending

Online peer-to-peer (P2P) lending platforms are marketplaces to exchange money online between individuals and businesses to borrow (borrowers), and those to lend (lenders). Although started only recently, such platforms are becoming increasingly recognized in the credit market due to simplified loan application processes, reduced overhead costs, and relatively low interest rates, all made possible by digital technologies (Forbes, 2017; Lin et al., 2013). Prosper.com and LendingClub.com, started in 2005 and 2006 respectively, remain the leaders in this "FinTech" unsecured loan market. Online P2P lending provides a suitable context to study the interplay between information asymmetry and platform governance design. P2P lending is an information-sensitive environment, where efficient exchanges between borrowers and lenders depend on the extent and quality of information available about each other (Iyer et al., 2015). A substantial literature on credit markets discusses the important role information plays in facilitating market transactions (Einav et al., 2013; Petersen & Rajan, 1994); integrating this literature with salient features of P2P lending offers researchers fruitful opportunities to study the effects of information asymmetry on platform effectiveness, and how platform owners may mitigate such problems through instituting proper governance policies in the form of decision right allocation.

An essential criterion for a lender to participate in a P2P lending platform is his/her ability to fund the loan, which usually doesn't have a minimum threshold. For a borrower, the threshold for participating in the platform is similar to a process of obtaining an unsecured loan from traditional financial institutions. To illustrate, Prosper in its SEC filing stated the following: "Except for our verification of the borrower member's identity, borrower listings are posted without our obtaining any documentation of the borrower's ability to afford the loan." This relatively "loose" process leads to a significant variation in the kind of borrowers listing loan requests, and in lenders' ability to process the information associated with such listings. As far as borrowers are concerned, they are drawn to P2P lending because of many potential advantages offered. Lenders, however, will need to decide on whether to make a loan through the platform to a borrower, whose identity is not entirely known to them. Such information gap can present a substantial challenge to lenders and lead otherwise valuable transactions to fall through because of the so-called lemon problem (Akerlof, 1970).

Variations in how the pricing right (i.e., who has the right to set loan interest rate) is being allocated in online P2P lending is helpful to understand the importance of colocation of information and decision authority. The right to set price is one of the most important decision rights. Two pricing models have been used by online P2P lending platforms (Wei & Lin, 2017). One is the auctions model, where the lenders collectively determines the price of the transaction (loan interest rate) through an auction process. With this model, lenders make three decisions regarding a borrower's loan listings: (i) whom to lend to, (ii) how much to lend, and (iii) what is the price (interest rate). The other is the posted-price model, where the right to set price (loan interest rate) is retained by the platform itself. With this model, lenders still need to decide on (i) and (ii), but not on (iii). To summarize, the two models differ significantly in how a key decision right, the right to set price, is being allocated among platform participants. We argue that such differences have important implications for how platform owners may address the problem of information asymmetry surrounding loan transactions and affect platform market effectiveness, to be discussed below.

4.4 Hypotheses

4.4.1 Decision Right Allocation and Platform Market Effectiveness

Problems of information asymmetry can be severe in online P2P lending markets, where platforms facilitate transactions between borrowers and lenders in a double-blind fashion (Lin et al., 2013). Borrowers sign up on a P2P lending platform, create verifiable identities, and share identity and other private information with the platform in a way comparable to traditional financial institutions such as banks. However, by law, platforms "are prohibited from disclosing their [borrowers'] actual identities anywhere on the [...] website" (SEC, 2008). Thus, for lenders participating in online P2P markets, the decision process is substantially different from the traditional credit market where the banks as lenders can use all the information about borrowers available to them in making lending decisions. Lenders in online P2P markets therefore face a significant information gap about the identity and other private information of the borrowers that the platform has access to but cannot share with lenders.

How key decision rights are allocated among participants in a platform market can significantly shape the informational environment. As said, in online P2P lending, one of the most important decision rights is the pricing right, or the right to set loan interest rate (Einav et al., 2018; Wei & Lin, 2017). Consider the posted-price model discussed above. This model allows the platform owner to fully utilize its superior knowledge and access to borrowers' information. For example, P2P lending platforms can make use of the extensive credit records shared by borrowers in setting an interest rate for each borrower. To the extent that such records and other identity information cannot be shared with prospective lenders, retaining the pricing right with the platform, rather than giving the right to lenders collectively, as in the case of the auctions model, can mitigate the information problem facing prospective lenders and reduce frictions in the market. Another reason why retaining the pricing right with the platform may be beneficial to the platform market as a whole is that loan products are generally homogeneous and standardized. This, for instance, provides a contrast with listings of rental properties on Airbnb or VRBO where the property owners set the listing price themselves, accounting for the large heterogeneity in the product offerings due to location, appearance, quality, and service (Zhu & Iansiti, 2019). For these reasons, from the platform owner's perspective, the posted-price model should provide a superior way to mitigate information problems and improve platform market effectiveness.

From the lenders' perspective, with the posted-price model, the number of decisions to make in the lending process is reduced from three (which borrowers to lend to, how much to lend, what is the interest rate), as in the case of the auctions model, to two (which borrowers to lend to, how much to lend). For any individual lender, the cost of searching information and determining an appropriate interest rate for each borrower can be exorbitantly high. Decision making is a costly endeavor (Gibbons et al., 2013; Simon, 1979), and making one less complex decision such as determining loan interest rates means significant cost savings for lenders. With the auctions model that gives the pricing right to the lenders, each of which only has access to public information about borrowers and would need to undertake costly effort to price loans and bid for listings, prospective lenders may actually be discouraged from actively participating in the market. This in turn may lead to inefficiencies in exchanges between borrowers and lenders and reduced market effectiveness as a whole.

For borrowers, having the platform determine loan interest rates is also consistent with their interest. In theory, rules of optimal allocation of decision rights require that such rights be allocated to the party with the most complete information, which is the platform owner itself. If a party with less complete information, such as lenders, is given the pricing right instead, it is more likely to discount its offer price (Akerlof, 1970; Reuer et al., 2012). Such offer price discounting means higher loan interest rate, which is not in the interest of the borrowers. In scenarios where the problem of offer price discounting is very severe, potentially value-creating loan transactions could fall through (Akerlof, 1970), hurting the platform as a whole.

The theoretical arguments above, combining the perspectives of all three major parties in online P2P lending markets, suggest that allocating the pricing right to the platform will increase the effectiveness of the platform market. Thus, we hypothesize:

Hypothesis 1: *Allocation of the pricing right to the platform will increase the effectiveness of the online P2P lending platform.*

4.4.2 Role of Local Financial Information

Online platform markets, such as P2P lending, do not operate in a vacuum. A large stream of research has examined how offline, local environments may generate information that shapes the behaviors of platform participants and affects market effectiveness (Lanzolla & Frankort, 2016; Lin & Viswanathan, 2015). Relatedly, information provision in local financial markets has been shown to have a significant impact on the functioning and efficiency of credit markets (Berger et al., 2005; Einav et al., 2013).

Building on extant research, we argue that the effect of decision right allocation on the effectiveness of online P2P platforms will vary across regions that provide different amounts of local financial information. Here we focus on financial information that is more standardized in nature and available locally (Petersen & Rajan, 1994). Specifically, when more financial institutions operate in a region, greater amounts of financial information will be produced. Given its standardized nature, such information can be easily shared and is widely available among local borrowers and lenders, making its utilization more prevalent (Liberti & Petersen, 2018). As a result, research has shown that borrowers in those regions tend to have higher financial awareness with better financial habits, and that lenders in the regions also have greater financial knowledge and expertise (Butler et al., 2016).

We propose that the effect of allocating the pricing right to the platform proposed in Hypothesis 1 will be stronger in regions where greater financial information is available offline. Research on online and offline market interaction has shown that the “readiness” of the offline environment for an online product offering is an important, necessary condition (Forman et al., 2009). At the same time, studies have noted that it is critical that online offerings are aligned with the offline information environment (Brynjolfsson, Hu, & Rahman, 2009). Thus, when the online

P2P platform is given the right to price loan listings based on its superior information about the borrowers that cannot be publicly shared, it is more likely to be recognized by the "more informed" platform participants in regions with greater financial information available. These participants are also more likely to take advantage of the transaction opportunities on the platform. These arguments lead to the following moderation hypothesis:

Hypothesis 2: *Allocation of the pricing right to the platform will increase the effectiveness of the online P2P lending platform to a larger extent, when greater financial information is available locally offline.*

4.5 Data and Methods

4.5.1 Research Design and Identification Strategy

We create a quasi-experimental research design for testing the hypotheses. Specifically, our analysis employs data on borrowers and lenders (market participants or platform complementors) from Prosper.com and LendingClub.com, two leading P2P lending platforms in the U.S. In our analysis, Prosper.com is the "treated" platform, while LendingClub.com serves as the "control" platform. Since its inception in 2005, Prosper had been using auctions as its pricing model, where lenders bid for borrowers' loan listings, and thus the right to set loan interest rates is effectively allocated to the lenders collectively (Einav et al., 2018). On December 17th, 2010, Prosper filed a *Post-Effective Amendment to Form S-1* with the SEC, changing its auction-based model to a posted-price model, where interest rates are preset and determined solely by Prosper, based on its loan pricing algorithm to evaluate each prospective borrower's credit risk.[2] The SEC accepted the *Amendment* and issued a *Notice of Effectiveness* on December 20th.[3] Upon approval Prosper.com switched its pricing mechanism to the posted-price model. This change was effective immediately on the whole website on the same day, and was unexpected by market participants (Renton, 2010). Under the new pricing model, lenders no longer determine the loan rate via price discovery in an auction; instead, they simply choose whether or not to invest at the rate which Prosper assigns to the loan after it analyzes the borrower's credit reports and various financial information. In addition, this posted-price model on Prosper is essentially the same as that implemented by its rival, LendingClub, which has been implementing this model since its founding (see Wei & Lin, 2017, p. 4237). This context gives us a unique opportunity to study how an unexpected change in a salient governance policy of the platform will impact platform participants and platform market effectiveness.

4.5.2 Sample Construction

The quasi-experimental design involves construction of a panel dataset. To measure market-level effectiveness and to test the hypothesis that market effectiveness varies across regions with different levels of financial information available, we focus on geographic markets at the 3-digit zip code level. Specifically, to better identify the effects of Prosper's pricing policy change, we create a panel dataset focusing on loan listings within the four quarters before and after this change.

[2] See the Amendment:
https://www.sec.gov/Archives/edgar/data/1416265/000141626510000555/prosperposam310d22d10.htm
[3] See the SEC's Notice of Effectiveness:
https://www.sec.gov/Archives/edgar/data/1416265/999999999510003619/9999999995-10-003619-index.htm

In a robustness analysis to be reported later, we also test for other time windows surrounding the change. Therefore, the unit of analysis is geographic area (3-digit zip code) by quarter.

The data used for this study came from a variety of sources. Data on P2P lendings and characteristics of the two platforms, Prosper Marketplace (www.prosper.com) and LendingClub (www.lendingclub.com), were crawled from their websites, after devoting a substantial amount of effort. We restricted our sample to the period from January 2010 to December 2011, including four quarters before and four quarters after the quarter in which Prosper changed its pricing policy to a posted-price model. We complemented platform data with geographic market-level data. Specifically, we obtained data on local financial institutions from the Business Pattern Data provided by the U.S. Census Bureau. Data on demographics (age, race, origin, poverty level), earnings, educational attainment, and population size and density were obtained from the Census Bureau as well. Data on the dollar amount of deposits in bank branches located within each geographic area were collected from the Federal Deposit Insurance Corporation (FDIC), a U.S. government corporation that provides deposit insurance to lending institutions. Unemployment data were collected from the Bureau of Labor Statistics (BLS). In the next step, we used the ArcGIS software to aggregate and match all collected data to 979 three-digit zip code prefixes to identify each focal geographic market. The final dataset with complete information for analysis consists of 14,112 observations.

4.5.3 Variables and Measurement

Dependent variable. The dependent variable *Funding rate* is the ratio of the number of loans funded to the number of loan requests on a platform (Prosper.com or LendingClub.com) for a given 3-digit zip code in a quarter. Prior research indicates that the effectiveness of a platform depends on the platform owner's ability to make potential transactions happen among complementors on both sides (Evans & Schmalensee, 2016; Rochet & Tirole, 2003). In keeping with this idea, we use this measure, the rate of loan requests being funded by lenders, to capture the effectiveness of online P2P lending in a geographic market (Wei & Lin, 2017).

Explanatory variables. The research design lends itself to a difference-in-differences (DD) analysis (Meyer, 1995). The first indicator variable used in the DD analysis is *Prosper*, which identifies the platform where the loan process originates (*Prosper*=1 if Prosper.com; *Prosper*=0 if LendingClub.com). The other indicator variable is *After*, which identifies the period after the pricing policy change (*After*=1 if it is any quarter in 2011; *After*=0 if it is any quarter in 2010). The DD interaction term *Prosper x After* (DD) is then created to test H1 about the treatment effect of allocation of the pricing right to the platform. A positive coefficient on the DD term will provide support for the hypothesis.

Testing of H2 requires a measure of available local financial information. The extant literature on credit markets and online-offline interactions suggests that financial market outcomes are affected by the financial information available to decision makers (Morse, 2015). Drawing from prior research, we use the variable *Financial institutions* as a proxy of available local financial information, measured as the number of credit offering institutions (including banks, credit unions, and mortgage lenders, among others) located in the focal geographic area in a quarter (Liberti & Petersen, 2019). The larger the number of financial institutions in an area, the greater the amount of financial information available in the area. Interaction of this variable with the DD term, *DD*Financial institutions*, is then used to test H2. We expect the coefficient on the triple-DD term to be positive.

Control variables. We include a number of variables to control for the effects due to economic, informational, and demographic conditions specific to local geographic areas. At the geography level, we first include *Deposits*, which indicates the general financial strength in local areas (Butler et al., 2016). According to the FDIC, deposits are the overall amount of money a specific branch in a local market has in its checking, savings, and money market accounts. Second, we include *Local lenders*, measured as the percentage of lenders with branches in only one state (Petersen & Rajan, 1994). Prior studies show that local lenders invest considerably in acquiring informal, personalized, soft information, and that they rely on such information greatly in their lending decisions. Third, prior literature suggests that competition in local financial markets indicates greater financial information available locally, and that it also often correlates with transaction outcomes. Thus, we calculate the commonly used *Herfindahl-Hirschman Index* (*HHI*) to measure the level of local market concentration, as an inverse proxy of market competition. In addition, in keeping with prior research in online P2P and platform-based markets (Lin & Viswanathan, 2015; Morse, 2015; Seamans & Zhu, 2017), we include nine other economic, educational, and demographic covariate controls: *Unemployment* (unemployment rate of residents), *Population*, *Population density* (population divided by the size of the area), *Black race* (proportion of residents identifying their race as Black), *Hispanic origin* (proportion of residents identifying themselves as Hispanic), *Median earnings* (median income of residents), *Bachelor's degree* (proportion of Bachelor's degree holders), *Median age* (median age of residents), and *Poverty level* (proportion of families in the borrower's area with an income below the poverty level).

At the platform-geography level, we include 14 variables to further control for any systematic differences between the treated and control groups (see Morse, 2015). The following seven variables are calculated for each of the two platforms (Prosper and LendingClub): *Credit score*, *Debt-to-income ratio* (*DTI*), *Amount requested*, *Funded amount*, *Interest rate*, *Borrower income*, and *Credit inquiries*.

Finally, we include geography fixed effects at the 3-digit zip code level to capture time-invariant unobserved local market characteristics. We also include a full set of quarter fixed effects to control for any systematic macroeconomic conditions that may affect P2P lending. Table 3.1 reports the variable definitions and data sources. Table 3.2 reports the descriptive statistics and correlations.

4.5.4 Estimation Approach

We apply the DD technique and run fixed effects linear regressions to test whether the assignment of the pricing right to the P2P platform will increase platform market effectiveness (H1) and whether available local financial information strengthens this effect (H2).

4.6 Results

Before moving to the regression analysis, we compare the *Funding rate* of loans originated in Prosper and LendingClub in a univariate analysis. We find that the *Funding rate* for Prosper's markets increased by 31.26 percent on average, from 18.01 percent in the pre-treatment period to 49.27 percent in the post-treatment period. By contrast, the *Funding rate* for LendingClub's markets did not experience a material change (from 7.95 percent to 6.96 percent). Therefore, a simple "difference-in-differences" effect is a 32.26 percentage point increase in *Funding rate*. This result provides a first indication consistent with H1's prediction.

4.6.1 Analysis of DD Assumptions

For the DD design to be valid, the parallel trend assumption must hold (Angrist & Pischke, 2009), which means that the average outcome for the treated (Prosper) and control groups (LendingClub) would have followed parallel paths over time had the treatment (Prosper's pricing policy change) been absent. This assumption cannot be rejected according to our analysis. First, we used data before the policy change (four quarters in 2010) and tested statistically whether the treated and control groups would follow a similar path up to the point of treatment. As shown in Table 3.3, we found an insignificant coefficient on the interaction term between a linear time trend and the *Prosper* dummy, indicating that the parallel trend assumption cannot be rejected.

Second, we tested for the Ashenfelter's dip (Ashenfelter, 1978) by splitting the pre-treatment period (four quarters in 2010) into two sub-periods (two quarters each) and checking whether there was any significant difference-in-differences for the treated and control groups, given that Prosper was not "officially" treated until December 2010. As show in Table 3.4, we did not find any unexpected drop in the pre-treatment period, meaning that if the main regression results would be significant, they should not be caused by a pre-treatment drop in the dependent variable of the treated group.

4.6.2 Hypotheses Tests

Moving to results of hypotheses tests, Table 3.5 reports DD regression results for the determinants of *Funding rate*. In our baseline hypothesis (H1), we posit that a platform governance policy change involving the allocation of the pricing right to the platform will increase P2P market effectiveness. Model 1 reports a positive and highly significant coefficient ($p<0.001$) for the *DD* variable (*Prosper*After*), providing strong support for this hypothesis. This result shows that

Prosper witnesses a 32.2 percent increase in the percentage of loan requests being funded after the change, after adjusting for the concurrent changes in funding rates on the rival platform LendingClub. Hypothesis 2 identifies an important boundary condition under which the platform governance policy change in Prosper will have a greater or smaller effect on *Funding rate*. Specifically, H2 predicts that the amount of financial information available in the local offline environment will positively moderate the *DD* variable such that the main effect in H1 will be strengthened for geographic areas with more financial institutions. Consistent with this prediction, the triple-DD term (*DD*Financial Institutions*) in Model 2 is positive and highly significant ($p<0.001$).

4.6.3 Supplementary Analyses

We conducted several analyses to assess the robustness of our results and extend our understanding of the findings. First, we analyze for additional time windows surrounding Prosper's policy change regarding the pricing right. Specifically, we create three additional samples, including data from (i) three quarters before and after, (ii) two quarters before and after, and (iii) one quarter before and after the policy change. Table 3.6 provides a summary of the DD regression results for the three samples. As shown in the table below, all coefficients are highly significant ($p<0.001$), suggesting that the results are robust to the use of different time windows to create samples.

In the literature, it has been suggested that when local financial institutions are in greater competition with each other, more financial information is being produced and made available to decision makers (Butler et al., 2016). Thus, in a second robustness check, we experimented using the *Herfindahl-Hirschman Index* (*HHI*) as an inverse measure of market competition to interact with the DD term to test H2. We therefore expect the coefficient on this triple-DD term to be negative. As shown in Model 1 of Table 3.7 below, the coefficient on *DD*HHI* is negative and significant ($p<0.001$), as expected.

Third, our measure of financial institutions (in the main analysis) or market competition (in the robustness test above) can be considered a proxy of the so-called hard information. Given the different roles played by hard versus soft information suggested in the literature (Liberti & Petersen, 2019), we explored how soft information may have a different interaction effect on platform market effectiveness. Following previous literature using *Local lenders* as a proxy for soft information (Petersen & Rajan, 1994), we interact this variable with the DD term. As shown in Model 2 of Table 3.7, the coefficient on the tripe-DD term *DD*Local Lenders* is negative and significant ($p<0.001$). Prior research indicates that because soft information is relationship-specific to the transacting parties, such information is less used outside of the context where the relationship happens (Liberti & Petersen, 2019). Thus, it is possible that when the reallocation of the pricing right to the P2P platform happens, it is less likely to be recognized and acted upon by market participants in areas with greater soft information available; as a result, the effect of the policy change is weakened for such areas.

4.7 Discussion

4.7.1 Research Contributions

This study makes several research contributions. First, our study links emerging research on platform markets to classic corporate strategy research on allocation of decision rights (Adner, 2017; McIntyre & Srinivasan, 2017). A nexus of the two streams of research is platform governance (Baldwin & Woodward, 2009; Tiwana et al., 2010). While research has long emphasized decision right allocation as a core part of platform governance (Tiwana et al., 2010), we are the first to argue and show that through appropriate allocation of key decision rights, platform owners, as the "regulator" of platform organizations (Chu & Wu, 2019), helps mitigate problems of information asymmetry endemic to platform markets and enhance platform effectiveness in matching prospective borrowers and lenders. Our focus on decision right allocation and the governance role of platform owners is in keeping with pioneering strategy research on platforms as a new mode of economic organization (Baldwin & Woodward, 2009), and it complements the recent focus on platform access as a key dimension of platform governance (Boudreau, 2017; Parker & Van Alstyne, 2018). Our findings highlight that although related to platform access, decision right allocation itself is a critical part of platform governance design and appropriate allocation of key decision rights helps improve the odds of platform success.

Second, our research improves existing knowledge of allocation of decision rights, a topic core to corporate strategy and organization science. Numerous studies have examined how decision rights are allocated within firms (e.g., between headquarters and divisions) and in interfirm relationships (e.g., between alliance partners). We conduct one of the first studies to extend decision right research to platforms, which are a new organizational form combining salient features of hierarchies and markets and are becoming ubiquitous in the new economy. We move beyond much of the extant research focus on the antecedents of allocation of decision rights at a cross section (Ozmel et al., 2017), by investigating how *changes* in allocation may cause changes in organizational effectiveness through a quasi-experimental design. Relatedly, our theoretical arguments drawing from information economics provides a complement to extant decision right allocation studies' main theoretical focus on transaction cost economics, property rights theory, real options, and organization theory (Argyres & Silverman, 2004; Arruñada et al., 2001; Foss et al., 2011; Tong & Li, 2013; Vázquez, 2004).

Third, our study adds to a growing body of research highlighting the importance of considering the interdependencies between online and offline information environments when designing and studying digital business models (Teece & Linden, 2017; Adner et al., 2019). While prior studies show that complementors with firm-specific, heterogeneous resources and attributes respond differentially to platform design change (Kretschmer & Claussen, 2016), we argue and demonstrate that broad characteristics of the location of complementors can also shape business transactions on digital platform markets (Forman et al., 2009). In simple terms, location still matters substantially in today's digital world. In addition, our focus on the interaction effects between decision right allocation and local information sources complements existing research focus on locational attributes as signals to online transacting parties (Lanzolla & Frankort, 2016). Our findings therefore emphasize that platform governance be designed and evaluated in tandem with the physical environments in which platform participants are embedded.

4.7.2 Limitations and Future Research

This study has several limitations due to the research scope that can provide additional opportunities for future work. First, although platform governance manifests itself in multiple dimensions and mechanisms (Tiwana et al., 2010), we only focused on decision right allocation. In addition, decision rights come in many different forms, and our research design could only zoom in on the pricing right—the right to set prices. While arguably this is one of the most important decision rights in platform markets, future research on other types of rights (e.g., rights to adjust the interface or particular features of the platform, as in the case of Google's Android OS) will be a welcome contribution. Second and relatedly, we encourage future research to move beyond a focus on decision rights *per se*, to begin studying such rights in line with other dimensions of platform governance such as control and ownership. For instance, analysis of the antecedents and implications of decision rights should be conducted with an eye to platforms' access control policy. Some platforms (e.g., iOS) implement more strict access control than others (e.g., Android), yet they may still give a great deal of decision authority to complementors; in other words, platform access should not be viewed as a dichotomy of "open" versus "closed" or as falling on a singular dimension (Parker & Van Alstyne, 2018). Just as it is incorrect to assume that Android will keep all decision rights related to the platform to itself, it is not true that all decision rights related to the complements (e.g., apps) will reside with iOS app developers. Research that analyzes multiple aspects of platform governance such as these holds promise to significantly advance our existing knowledge of the orchestrating role of platform owners. Third, although we argued that the reallocation of the pricing right to the platform owner can reduce the effects of information asymmetries in online P2P markets, we were not able to directly measure the degree of such reduction, similar to prior related research (e.g., Lin & Viswanathan, 2015). In addition, data limitations restricted our ability to directly examine the behaviors of borrowers and lenders, because 1) for both Prosper and LendingClub, information on borrowers and sellers were only available for loan listings that were eventually funded (thus we couldn't compare the participants in funded loan listings with those in unfunded loan listings), and 2) information on lenders were not at all available for LendingClub (though partially available for Prosper). We encourage future studies to delve into some of the theorized mechanisms by collecting finer-grained data from other sources or by employing other methods such as surveys or field studies.

4.8 Conclusion

Platform owners play an important governance role in orchestrating complementors' participation in the platform in the presence of asymmetric information. This study incorporates foundational corporate strategy research on decision right allocation into emerging research on platform governance by arguing that such orchestration can be achieved through appropriate allocation of key decision rights between the platform and the complementors. By exploiting Prosper's unexpected switch to the posted-price model where the platform takes back the right to set loan interest rates, we show that the allocation of a key decision right that better aligns information with incentives leads to an increase in platform market effectiveness, and that this effect varies across geographic markets providing heterogeneous financial information. In an economy in which digital platform organizations are growing in prominence amidst information disparity between platform participants, we hope that our study will stimulate more future research on the relationship between corporate strategy, platform governance, and organizational effectiveness.

4.9 References

Adner, R. 2017. Ecosystem as structure: An actionable construct for strategy. *Journal of Management*, 43(1): 39-58.

Adner, R., Puranam, P., & Zhu, F. 2019. What is different about digital strategy? *Strategy Science*, 4(4): 253-261.

Akerlof, G.A. 1970. The market for "lemons": Qualitative uncertainty and the market mechanism. *Quarterly Journal of Economics*, 84: 488-500.

Angrist, J.D., & Pischke, J. 2009. *Mostly Harmless Econometrics: An Empiricist's Companion*. Princeton University Press.

Argyres, N.S., & Silverman, B.S. 2004. R&D, organization structure, and the development of corporate technological knowledge. *Strategic Management Journal*, 25: 929-958.

Arruñada, B., Garicano, L., & Vázquez, L. 2001. Contractual allocation of decision rights and incentives: The case of automobile distribution. *Journal of Law, Economics, & Organization*, 17(1): 257-284.

Ashenfelter, O. 1978. Estimating the effect of training programs on earnings. *Review of Economics & Statistics*, 60(1): 47-57.

Athey, S., & Roberts, J. 2001. Organizational design: Decision rights and incentive contracts. *American Economic Review*, 91(2): 200-205.

Baldwin, C.Y., & Woodard, C.J. 2009. The architecture of platforms: A unified view. Gawer, A. (Ed.) *Platforms, Markets and Innovation*, p. 19-44. Cheltenham, UK and Northampton, US: Edward Elgar.

Berger, A.N., Miller, N.H., Petersen, M.A., Rajan, R.G., & Stein, J.C. 2005. Does function follow organizational form? Evidence from the lending practices of large and small banks. *Journal of Financial Economics*, 76(2): 237-269.

Boudreau, K.J. 2017. Platform boundary choices & governance: Opening-up while still coordinating and orchestrating. *Advances in Strategic Management*, 37: 227-297.

Boudreau, K.J., & Hagiu, A. 2009. Platforms rules: Multi-sided platforms as regulators. Gawer A. (Ed.) *Platforms, Markets and Innovations*, p. 163-191. Cheltenham, UK and Northampton, US: Edward Elgar.

Brynjolfsson, E., Hu, Y., & Rahman, M.S. 2009. Battle of the retail channels: How product selection and geography drive cross-channel competition. *Management Science*, 55(11): 1755-1765.

Butler, A.W., Cornaggia, J., & Gurun, U.G. 2016. Do local capital market conditions affect consumers' borrowing decisions? *Management Science*, 63(12): 4175-4187.

Chevalier, J. A., & Mayzlin, D. 2006. The effect of word of mouth on sales: Online book reviews. *Journal of Marketing Research*, 43(3): 345-354.

Chu, L.Y., & Wu, B. 2019. *Designing online platforms for offline services: The bigger, the better*? Working Paper, University of Southern California and University of Michigan.

Claussen, J., Kretschmer, T., & Mayrhofer, P. 2013. The effects of rewarding user engagement: The case of Facebook apps. *Information Systems Research*, 24(1): 186-200.

Cramer, J., & Krueger, A.B. 2016. Disruptive change in the taxi business: The case of Uber. *American Economic Review*, 106(5): 177-182.

Einav, L., Farronato, C., Levin, J., & Sundaresan, N. 2018. Auctions versus posted prices in online markets. *Journal of Political Economy*, 126(1): 178-215.

Einav, L., Jenkins, M., & Levin, J. 2013. The impact of credit scoring on consumer lending. *RAND Journal of Economics*, 44(2): 249-274.

Evans, D.S., & Schmalensee, R. 2016. *Matchmakers: The New Economics of Multisided Platforms*. Harvard Business School Publishing, Boston, MA.

Fama, E.F., & Jensen, M.C. 1983. Separation of ownership and control. *Journal of Law & Economics*, 26(2): 301-325.

Forbes. 2017. Using peer-to-peer lending as a method for startup growth. https://www.forbes.com/sites/theyec/2017/07/26/using-peer-to-peer-lending-as-a-method-for-startup-growth/#19d7e63f50f3. Accessed: 2020-1-28.

Forman, C., Ghose, A., & Goldfarb, A. 2009. Competition between local and electronic markets: How the benefit of buying online depends on where you live. *Management Science*, 55(1): 47-57.

Foss, N.J., Laursen, K., & Pedersen, T. 2011. Linking customer interaction and innovation: The mediating role of new organizational practices. *Organization Science*, 22(4): 980-999.

Gibbons, R., Matouschek, N., & Roberts, J. 2013. Decisions in organizations. Gibbons, R., & Roberts, J. (Eds.) *The Handbook of Organizational Economics*, p. 373-431. Princeton University Press.

Hosanagar, K., Fleder, D., Lee, D., & Buja, A. 2013. Will the global village fracture into tribes? Recommender systems and their effects on consumer fragmentation. *Management Science*, 60(4): 805-823.

Iyer, R., Khwaja, A.I., Luttmer, E.F., & Shue, K. 2016. Screening peers softly: Inferring the quality of small borrowers. *Management Science*, 62(6): 1554-1577.

Jensen, M.C., & Meckling, W.H. 1992. Specific and general knowledge, and organizational structure. Werin, L., & Wijkander, H. (Eds.), *Contract Economics*, p. 251-274. Oxford: Blackwell.

Jin, G.Z., & Kato, A. 2007. Dividing online and offline: A case study. *Review of Economic Studies*, 74(3): 981-1004.

Kretschmer, T., & Claussen, J. 2016. Generational transitions in platform markets: The role of backward compatibility. *Strategy Science*, 1(2): 90-104.

Lanzolla, G., & Frankort, H.T.W. 2016. The online shadow of offline signals: Which sellers get contacted in online B2B marketplaces? *Academy of Management Journal*, 59(1): 207-231.

Liberti, J.M., & Petersen, M.A. 2019. Information: Hard and soft. *Review of Corporate Finance Studies*, 8(1): 1-41.

Liebeskind, J.P. 1996. Knowledge, strategy, and the theory of the firm. *Strategic Management Journal*, 17: 93-107.

Lin, M., Prabhala, N.R., & Viswanathan, S. 2013. Judging borrowers by the company they keep: Friendship networks and information asymmetry in online peer-to-peer lending. *Management Science*, 59(1): 17-35.

Lin, M., & Viswanathan, S. 2015. Home bias in online investments: An empirical study of an online crowdfunding market. *Management Science*, 62(5): 1393-1414.

McIntyre, D.P., & Srinivasan, A. 2017. Networks, platforms, and strategy: Emerging views and next steps. *Strategic Management Journal*, 38(1): 141-160.

Meyer, B.D. 1995. Natural and quasi-experiments in economics. *Journal of Business & Economic Statistics*, 13(2): 151-161.

Morse, A. 2015. Peer-to-peer crowdfunding: Information and the potential for disruption in consumer lending. *Annual Review of Financial Economics*, 7: 463-482.

Ozmel, U., Yavuz, D., Reuer, J.J., & Zenger, T. 2017. Network prominence, bargaining power, and the allocation of value capturing rights in high-tech alliance contracts. *Organization Science*, 28(5): 947-964.

Parker, G., & Van Alstyne, M. 2018. Innovation, openness, and platform control. *Management Science*, 64(7): 3015-3032.

Peterson, M.A., & Rajan, R.G. 1994. The benefit of firm creditors relationship: Evidence from small business data. *Journal of Finance*, 49(1): 3-37.

Renton, P. 2010. Prosper.com ending their auction process Dec 19th. https://www.lendacademy.com/prosper-com-ending-their-auction-process-dec-19th/. Accessed: 2020-1-28.

Reuer, J.J. 2009. Organizational economics insights from acquisitions research. *Advances in Strategic Management*, 26: 241-265.

Reuer, J.J., Tong, T.W., & Wu, C.-W. 2012. A signaling theory of acquisition premiums: Evidence from IPO targets. *Academy of Management Journal*, 55(3): 667-683.

Rochet, J.-C., & Tirole, J. 2003. Platform competition in two-sided markets. *Journal of the European Economic Association*, 1(4): 990-1029.

Seamans, R., & Zhu, F. 2017. Repositioning and cost-cutting: The impact of competition on platform strategies. *Strategic Management Journal*, 2(2): 83-99.

SEC. 2008. In the Matter of Prosper Marketplace, Inc. https://www.sec.gov/litigation/admin/2008/33-8984.pdf. Accessed: 2020-1-28.

Simon, H.A. 1979. Rational decision making in business organizations. *American Economic Review*, 69(4): 493-513.

Teece, D.J., & Linden, G. 2017. Business models, value capture, and the digital enterprise. *Journal of Organization Design*, 6:8. DOI 10.1186/s41469-017-0018-x.

Tiwana, A., Konsynski, B., & Bush, A.A. 2010. Platform evolution: Coevolution of platform architecture, governance, and environmental dynamics. *Information Systems Research*, 21(4): 675-687.

Tong, T.W., & Li, S. 2013. The assignment of call option rights between partners in international joint ventures. *Strategic Management Journal*, 34(10): 1232-1243.

Vázquez, X.H. 2004. Allocating decision rights on the shop floor: A perspective from Transaction cost economics and organization theory. *Organization Science*, 15(4): 463-480.

Wareham, J., Fox, P.B., & Giner, J.L.C. 2014. Technology ecosystem governance. *Organization Science*, 25(4): 1195-1215.

Wei, Z., & Lin, M. 2017. Market mechanisms in online peer-to-peer lending. *Management Science*, 63(12): 4236-4257.

Williamson, O.E. 1975. *Markets and Hierarchies: Analysis and Antitrust Implications*. Free Press: New York.

Zhu, F., & Iansiti, M. 2019. Why some platforms thrive and others don't. *Harvard Business Review*, January-February: 119-125.

Zhu, F., & Liu, Q. 2018. Competing with complementors: An empirical look at Amazon.com. *Strategic Management Journal*, 39: 2618-2642.

Table 4.1 Variables and Definition

Variables	Definition
Dependent variable	
Funding Rate	Number of the loans approved divided by the number of loan requests in a geographic market in a quarter
Explanatory variables	
Prosper	A dummy variable, which equals one if the Proper.com is the platform where the lending happens, and zero if LendingClub.com
After	A dummy variable, which equals one if the lending happens after the fourth quarter of 2010, and zero if it is in the fourth quarter of 2010 or before
Moderator	
Financial Institutions	The number of credit offering institutions in thousands (including banks, credit unions, and mortgage lenders among others) in the area. Source: Census Bureau
Control variables (geography-level)	
Deposits	The dollar amount (in millions) of deposits in bank branches. Source: FDIC
Local Lenders	Percentage of lenders with branches in only one state. Source: Census Bureau
HHI	Herfindahl–Hirschman Index calculated by market share of deposits of each bank in a particular geographic market. Source: FDIC
Unemployment	The unemployment rate of the residents. Source: Bureau of Labor Statistics
Population	The population (in log). Source: Census Bureau
Population Density	The area's population divided by the area's size. Source: Census Bureau
Black Race	Proportion of residents who identify their race as Black. Source: Census Bureau
Hispanic Origin	Proportion of residents who identify themselves as Hispanic. Source: Census Bureau
Median Earnings	The median income in dollar amount (in thousands) of residents. Source: Census Bureau
Bachelor's Degree	The proportion of Bachelor's degree holders. Source: Census Bureau
Median Age	The median age of residents. Source: Census Bureau
Poverty Level	The proportion of families in the borrower's local area whose income is lower than the poverty level. Source: Census Bureau
Control variables (platform-geography level); Source: Prosper.com and LendingClub.com	
Prosper Credit Score	Average credit score of loan requests on Prosper
Prosper DTI	Average debt-to-income ratio of loan requests on Prosper
Prosper Amount Requested	Average loan amount in dollars (in 10,000) requested for loan listings on Prosper
Prosper Funded Amount	Average loan amount in dollars (in 10,000) requested for the funded loans on Prosper
Prosper Interest Rate	Average interest rate (in percentage) of the funded loans on Prosper
Prosper Income	Average income in dollars (in 10,000) of the borrowers of the funded loans on Prosper
Prosper Inquiries	Average number of credit related inquiries in the last six months by funded loan borrowers of Prosper
LC Credit Score	Average credit score of loan requests on LendingClub
LC DTI	Average debt-to-income ratio of loan requests on LendingClub
LC Amount Requested	Average loan amount in dollars (in 10,000) requested for loan listings on LendingClub
LC Funded Amount	Average loan amount in dollars (in 10,000) requested for the funded loans on LendingClub
LC Interest Rate	Average interest rate (in percentage) of the funded loans on LendingClub
LC Income	Average income in dollars (in 10,000) of the borrowers of the funded loans on LendingClub
LC Inquiries	Average number of credit related inquiries in the last six months by funded loan borrowers of LendingClub

Table 4.2 Descriptive Statistics and Correlations

	Variables	Mean	S.D.	1	2	3	4	5	6	7	8	9	10	11	12	13
1	Financial Institutions	170.99	163.39													
2	HHI	0.63	0.98	**-0.08**												
3	Deposits	8.97	23.80	**0.56**	**0.28**											
4	Local Lenders	0.11	0.10	**-0.35**	**-0.05**	**-0.18**										
5	Unemployment	9.16	2.27	**0.13**	**-0.07**	0.02	**-0.32**									
6	Population	347.19	370.32	**0.92**	**-0.10**	**0.49**	**-0.35**	**0.20**								
7	Population Density	1.37	5.47	**0.15**	**0.18**	**0.43**	**-0.15**	0.03	**0.19**							
8	Black Race	10.65	12.76	**0.22**	**0.07**	**0.13**	**-0.27**	**0.20**	**0.21**	**0.13**						
9	Hispanic Origin	11.05	13.75	**0.21**	**0.04**	**0.16**	**-0.13**	**0.18**	**0.34**	**0.18**	-0.01					
10	Median Earnings	34.37	7.83	**0.31**	**0.13**	**0.28**	**-0.29**	**-0.16**	**0.30**	**0.42**	0.01	**0.07**				
11	Bachelor's Degree	25.19	10.53	**0.31**	**0.13**	**0.29**	**-0.29**	**-0.24**	**0.26**	**0.39**	0.03	**0.06**	**0.82**			
12	Poverty Level	10.77	4.61	**-0.07**	**0.09**	-0.02	-0.03	**0.43**	-0.03	0.02	**0.41**	**0.23**	**-0.58**	**-0.51**		
13	Median Age	38.38	3.56	**-0.23**	**-0.15**	**-0.15**	**0.20**	-0.03	**-0.27**	**-0.15**	**-0.33**	**-0.42**	**-0.12**	**-0.16**	**-0.29**	
14	Prosper Amount Requested	0.46	0.42	**0.33**	**-0.07**	**0.11**	**-0.25**	**0.14**	**0.32**	**-0.03**	**0.15**	**0.08**	**0.23**	**0.22**	**-0.12**	**-0.12**
15	Prosper DTI	0.17	0.17	**0.21**	**-0.08**	**0.03**	**-0.18**	**0.11**	**0.19**	**-0.08**	**0.13**	0.02	0.03	0.03	-0.02	**-0.10**
16	Prosper Credit Score	475.72	337.69	**0.39**	**-0.12**	**0.11**	**-0.32**	**0.18**	**0.38**	**-0.06**	**0.20**	**0.09**	**0.21**	**0.20**	**-0.11**	**0.17**
17	Prosper Funded Amount	0.30	0.36	**0.38**	-0.02	**0.17**	**-0.24**	**0.11**	**0.37**	-0.01	**0.16**	**0.08**	**0.21**	**0.20**	**-0.10**	**-0.17**
18	Prosper Interest Rate	0.12	0.12	**0.38**	**-0.08**	**0.11**	**-0.26**	**0.15**	**0.37**	**-0.05**	**0.17**	**0.08**	**0.16**	**0.14**	**-0.09**	**-0.18**
19	Prosper Income	3.48	8.01	**0.20**	**0.04**	**0.10**	**-0.15**	**0.05**	**0.20**	0.01	**0.09**	**0.09**	**0.16**	**0.13**	**-0.05**	**-0.09**
20	Prosper Inquiries	0.47	0.89	**0.23**	**-0.06**	**0.09**	**-0.17**	**0.12**	**0.25**	-0.01	**0.08**	**0.08**	**0.16**	**0.10**	**-0.09**	**-0.11**
21	LC Amount Requested	1.02	0.44	**0.16**	0	**0.09**	**-0.24**	**0.20**	**0.16**	**0.12**	0.03	**0.12**	**0.24**	**0.16**	-0.04	**-0.05**
22	LC DTI	0.20	0.11	0	-0.02	-0.03	**-0.07**	**0.10**	0	**-0.07**	-0.02	0.01	-0.03	**-0.07**	0.04	-0.01
23	LC Credit Score	540.32	172.91	**0.16**	-0.03	**0.09**	**-0.26**	**0.21**	**0.18**	**0.07**	**0.06**	**0.13**	**0.19**	**0.15**	-0.01	**-0.09**
24	LC Funded Amount	0.97	0.67	**0.11**	**-0.04**	**0.05**	**-0.16**	**0.18**	**0.14**	**0.07**	**0.11**	**0.15**	**0.17**	**0.11**	0	**-0.05**
25	LC Interest Rate	0.08	0.06	**0.30**	**-0.06**	**0.17**	**-0.29**	**0.20**	**0.35**	**0.12**	**0.13**	**0.22**	**0.29**	**0.25**	**-0.09**	**-0.17**
26	LC Income	4.26	4.29	**0.28**	0.03	**0.17**	**-0.23**	**0.12**	**0.30**	**0.12**	**0.10**	**0.16**	**0.34**	**0.26**	**-0.13**	**-0.14**
27	LC Inquiries	0.74	0.93	**0.14**	**-0.04**	**0.09**	**-0.12**	**0.14**	**0.16**	**0.03**	**0.07**	**0.08**	**0.12**	**0.06**	-0.02	**-0.08**

	Variables	14	15	16	17	18	19	20	21	22	23	24	25	26
15	Prosper DTI	**0.56**												
16	Prosper Credit Score	**0.81**	**0.70**											
17	Prosper Funded Amount	**0.56**	**0.32**	**0.57**										
18	Prosper Interest Rate	**0.38**	**0.46**	**0.61**	**0.61**									
19	Prosper Income	**0.22**	**0.14**	**0.30**	**0.37**	**0.36**								
20	Prosper Inquiries	**0.22**	**0.21**	**0.36**	**0.33**	**0.55**	**0.25**							
21	LC Amount Requested	**0.15**	**0.09**	**0.17**	**0.16**	**0.13**	**0.08**	**0.14**						
22	LC DTI	**0.07**	**0.07**	**0.09**	**0.04**	**0.04**	0.01	0.02	**0.33**					
23	LC Credit Score	**0.20**	**0.15**	**0.25**	**0.15**	**0.16**	**0.09**	**0.13**	**0.67**	**0.54**				
24	LC Funded Amount	**0.12**	0.02	**0.15**	**0.12**	**0.10**	**0.08**	**0.09**	**0.24**	**0.17**	**0.33**			
25	LC Interest Rate	**0.27**	**0.17**	**0.34**	**0.22**	**0.24**	**0.14**	**0.17**	**0.27**	**0.14**	**0.42**	**0.32**		
26	LC Income	**0.23**	**0.13**	**0.28**	**0.22**	**0.22**	**0.14**	**0.13**	**0.23**	**0.10**	**0.33**	**0.26**	**0.67**	
27	LC Inquiries	**0.13**	**0.12**	**0.20**	**0.09**	**0.14**	**0.06**	**0.10**	**0.14**	**0.10**	**0.24**	**0.18**	**0.59**	**0.42**

N=14,112. All bold values are significant at the p<0.05 level, two-tailed test.

Table 4.3 Test for Parallel Trend in the Pre-Treatment Period

Variables	Model 1
Prosper*Quarter	0.596
	(1.102)
Controls	Yes
Quarter Fixed Effects	Yes
Geography Fixed Effects	Yes
N	3,528
R^2	0.445

Note: Standard errors clustered at the geography level are reported in parentheses.

Table 4.4 Test for Ashenfelter Dip in the Pre-Treatment Period

Variables	Model 1
DD (Prosper*After)	0.596
	(1.369)
Controls	Yes
Quarter Fixed Effects	Yes
Geography Fixed Effects	Yes
N	3,528
R^2	0.445

Note: Standard errors clustered at the geography level are reported in parentheses.

Table 4.5 DD Regression Results for Funding Rate (+/- 4 Quarters)

Variables	Model 1		Model 2	
Prosper	10.060	(0.434)	10.060	(0.434)
After	-4.870	(0.727)	-4.038	(0.724)
DD (Prosper*After)	**32.249**	**(0.814)**	**24.135**	**(1.068)**
DD * Financial Institutions			**0.048**	**(0.003)**
Financial Institutions	-0.067	(0.013)	0.010	(0.014)
Deposits	0.012	(0.032)	-0.132	(0.049)
Local Lenders	-56.655	(21.140)	-46.990	(20.865)
Unemployment	-0.578	(0.235)	-0.459	(0.235)
Population	-0.177	(0.038)	0.042	(0.043)
Population Density	-0.714	(0.413)	-0.154	(0.416)
Black Race	10.908	(3.063)	-6.795	(3.393)
Hispanic Origin	-0.952	(0.912)	0.828	(0.930)
Median Earnings	1.223	(0.640)	-1.127	(0.669)
Bachelor's Degree	0.086	(1.307)	1.379	(1.317)
Poverty Level	15.937	(5.677)	-8.158	(6.039)
Median Age	8.952	(2.460)	-5.129	(2.716)
Prosper Amount Requested	-11.446	(0.673)	-11.262	(0.668)
Prosper DTI	-9.586	(1.415)	-9.025	(1.409)
Prosper Credit Score	0.031	(0.001)	0.030	(0.001)
Prosper Funded Amount	12.590	(0.764)	12.182	(0.759)
Prosper Interest Rate	44.326	(2.366)	45.209	(2.367)
Prosper Income	0.001	(0.029)	0.002	(0.032)
Prosper Inquiries	-0.109	(0.197)	-0.144	(0.198)
LC Amount Requested	0.081	(0.441)	0.182	(0.432)
LC DTI	-3.146	(1.770)	-3.284	(1.745)
LC Credit Score	0.001	(0.001)	0.001	(0.001)
LC Funded Amount	0.395	(0.315)	0.534	(0.312)
LC Interest Rate	44.194	(4.456)	46.630	(4.430)
LC Income	0.044	(0.046)	0.042	(0.046)
LC Inquiries	-0.097	(0.212)	-0.014	(0.211)
Constant	-467.176	(122.521)	251.767	(136.199)
Quarter Fixed effects	Yes		Yes	
Geography Fixed effects	Yes		Yes	
R Squared	0.557		0.570	

Note: N=14,112. Standard errors clustered at the geography level are reported in parentheses. *p* values reported in the text are based on two-tailed test.

Table 4.6 Summary of DD Regression Results for *Funding Rate* for Different Time Windows

Variables	Length of Time Windows		
	+/- 3 quarters	+/- 2 quarters	+/- 1 quarter
DD (Prosper*After)	**26.760**	**23.200**	**12.840**
	(0.940)	**(1.189)**	**(0.979)**
DD*Financial Institutions	**0.048**	**0.047**	**0.071**
	(0.004)	**(0.005)**	**(0.009)**
Other Controls	Yes	Yes	Yes
Quarter Fixed Effects	Yes	Yes	Yes
Geography Fixed Effects	Yes	Yes	Yes
No. of Observations	10,584	7,056	3,528

Note: This table summarizes results of robustness checks using three other samples of different time windows (+/- 3 quarters, +/- 2 quarters, and +/- 1 quarter, respectively). Model specifications are the same as the main analyses in Table 3.5. Standard errors clustered at the geography level are reported in parentheses. *p* values reported in the text are based on two-tailed test.

Table 4.7 Summary of DD Regression Results using *HHI* and *Local Lenders* as a Moderator

Variables	Model 1	Model 2
DD (Prosper*After)	**33.821**	**35.410**
	(0.889)	**(1.041)**
DD*HHI	**-2.443**	--
	(0.624)	--
DD*Local Lenders	--	**-2.135**
	--	**(0.464)**
Other Controls	Yes	Yes
Quarter Fixed Effects	Yes	Yes
Geography Fixed Effects	Yes	Yes
R^2	0.565	0.568

Note: N=14,112. Standard errors clustered at the geography level are reported in parentheses. *p* values reported in the text are based on two-tailed test.

CHAPTER 5. DOES PLATFORM GATEKEEPING AFFECT COMPLEMENTORS' STRATEGY TO PROFIT FROM INNOVATION?

"The apps phenomenon began with the iPhone. When it first came out in early 2007, there were no apps you could buy from outside developers, and Jobs initially resisted allowing them. He didn't want outsiders to create applications for the iPhone that could mess it up, infect it with viruses, or pollute its integrity... Jobs soon figured out that there was a way to have the best of both worlds. He would permit outsiders to write apps, but they would have to meet strict standards, be tested and approved by Apple, and be sold only through the iTunes Store. It was a way to reap the advantage of empowering thousands of software developers while retaining enough control to protect the integrity of the iPhone and the simplicity of the customer experience... The App Store for the iPhone opened on iTunes in July 2008."

– Isaacson (2011: 501)

5.1 Introduction

in a new way for a new market. Thus, in creating the App Store, Apple outsourced some (but not all) of its corporate strategy decisions to the world at large. This outsourcing required a trade-off between Apple and independent software developers: On one hand, it dramatically increased the potential range of functions that the iPhone could perform, and Apple is able to do so without the need to make costly and risky investments in innovating those functions by itself. On the other hand, it also required Apple to surrender some degree of control over the user experience to those independent software developers, thereby potentially threatening the quality of that experience – which, if damaged, could undermine the platform's value proposition.

This tension underlying Apple's creation of the iPhone App Store illustrates a general problem for platform-based businesses. Both sides of the market are critical for a platform's value proposition to materialize (Adner, 2017; Baldwin & Woodard, 2009; McIntyre & Srinivasan, 2017). On one side, a user benefits from having a wide variety of offerings from complementors, since this may increase the likelihood of finding one that is a close match to her unique needs and preferences, and may also allow her to benefit from competition by complementors, such as higher quality, cutting-edge innovation, or even just lower prices. On the other side, a complementor benefits from the agglomeration of users, since this may increase potential revenue, enable exploitation of scale economies, and provide access to a wider range of user feedback at a quicker pace. Nevertheless, the realization of these benefits for both sides – and hence, the value created by the platform – may be undermined or impeded by adverse selection problems (Akerlof, 1970). As Tadelis (2016) noted, in digital marketplaces, it has always been a challenge to alleviate information asymmetries where "strangers who had never transacted with one another, and who may have been thousands of miles apart" often need to interact with each other.

Platforms have developed a wide variety of solutions to this information asymmetry problem, with the goal of enabling complementors to build a "realistic revenue architecture" (Kapoor & Teece, 2021; Teece, 2010), while simultaneously guarding against threats to the users' experience that might undermine the platform's value proposition (Boudreau, 2017; Boudreau & Hagiu, 2009; Evans & Schmalensee, 2016). While much research has focused on solutions such as user-generated feedback mechanisms (e.g., ratings, reviews), researchers have only just recently started to consider how platforms utilize governance mechanisms to mitigate informational frictions that threaten the realization of their value propositions (Chevalier & Mayzlin, 2006; Forman et al., 2008; Jin & Kato, 2007). For example, studies have carefully examined how platforms use access control mechanisms to shape complementors' value creation activities (Boudreau, 2010; Parker & Van Alstyne, 2018), yet evidence remains scant on how such mechanisms could be used to mitigate problems of information asymmetry and shape complementors' strategy to profit from innovation.

In this paper, we focus on one such access control mechanism, platform gatekeeping, and examine how its deployment (or failure to deploy) affects informational frictions, which in turn influence the complementors' strategies to profit from innovation. Gatekeeping refers to a platform's "bouncer rights" to control both what (complements) and who (complementors) are allowed on a platform; it is an explicit and frequently used access control mechanism, and has proven effective in providing platform owners with a lever of control (Tiwana, 2013; Zhang *et al.*, 2020). In particular, gatekeeping provides an effective solution to limit an array of information-related hazards that both sides of the platform organizations are likely exposed to. For example, gatekeeping helps to restrict access to complementors who may infringe intellectual property with copycats and software crackers (Wang *et al.*, 2018), thereby protecting developers from exploitation by other developers. Similarly, it also helps to weed out developers who threaten users with hazards that are largely invisible to them, such as apps that either contain malware, abuse users' privacy, or interfere with operating system functions and/or with other apps (Tiwana, 2013). So, gatekeeping can shield users from "lemons problems," thereby incentivizing them to participate in transactions with complementors that might otherwise be subject to market failure.

In addition to these intended effects on the incentives of users, gatekeeping may also have unintended effects on the incentives of complementors as well – in particular, effects on their incentives to engage in different strategies for value appropriation. In order for complementors to innovate in the way that is needed to build a platform's value proposition to users, there must be a viable "appropriability regime" that enables them to profit from innovation (Pisano, 2006; Teece, 1986; Teece, 2010). In digital platforms, a complementor can often engage in a variety of monetization mechanisms – e.g., direct sales, initial free trial, "freemium" (selling upgrades to an initially free product), advertiser support, subscriptions, or sale of user data to third parties – each of which represents a different strategy for value appropriation, carrying different implications for the complementor's relationship with users, the platform, and third parties like advertisers and data aggregators.

In this regard, each firm's choice of monetization method can be a key element in the activity system underlying its strategy (Porter, 1996), in which case the effectiveness of that choice would depend critically on its fit with other elements of the firm's activity system, with the firm's overall market positioning, and with the needs of customers and other relevant constituencies. For example, Casadesus-Masanell and Zhu (2013) shows that successful adoption of a sponsor-based monetization mechanism will be dependent on how a firm differentiates itself in terms of product quality. Similarly, Zott and Amit (2008) shows that novel monetization methods may enable a firm to successfully straddle two potentially conflicting product market strategies such as differentiation and cost leadership, when such straddling would otherwise fail.

Marrying organizational governance research with the emerging study of platform-based organizations, we argue that platforms can leverage gatekeeping as a governance instrument to mitigate information asymmetry, which in turn shapes complementors' monetization strategies. Specifically, we suggest that platform gatekeeping has two effects on complementors' strategies for value appropriation: First, by mitigating adverse selection problems for users, gatekeeping raises users' willingness to pay for a complementor's products – similar to how providing a warranty on a used car mitigates concerns about the lemons problem to a point where market failure can be avoided. Second, since gatekeeping provides a form of screening by the platform, it alleviates the need for users to conduct their own separate screening of complementors' offerings. So, in the absence of such gatekeeping, users may prefer a complementor who offers a "try before you buy" monetization method (e.g., initial free trial or freemium), in order to have the opportunity to conduct their own screening – similar to the way that a used car buyer might want a no-risk free return period, or at least an opportunity to have an independent mechanic conduct an inspection. Therefore, weak platform gatekeeping reduces complementors' opportunities to profit from innovation before users can experience the products.

To empirically test our predictions, we focus on Apple's iOS and Google's Android, two leading mobile app platforms in the world. Compared to the Google Play Store, the iOS App Store is well-known to have relatively strict guidelines for app developers to gain platform access and exercise high levels of control in their gatekeeping decisions. More importantly, unlike Apple iOS, Android places very limited gatekeeping restrictions on users' ability to obtain apps from other independent app stores, such as the Samsung Galaxy Store, Amazon Appstore, Huawei App Market Store, and numerous others. It is also widely recognized that paid apps are much more common, command significantly higher prices, and generate substantially more revenue for developers on the iOS App Store than on the Google Play Store, whereas app developers rely more heavily on monetization via advertising and in-app purchases (e.g., freemium) on the Google Play Store than on the iOS App Store. We examine whether these two observations about iOS versus Android – i.e., the difference between platforms in their gatekeeping strength, and the differences between them in app developers' choices about value appropriation strategies – are causally connected, from the former to the latter. In order to accomplish this goal in an empirically rigorous way, we leverage a quasi-natural experiment – namely, the jailbreak of iOS 10, which (timing-wise) was an exogenous breakdown of Apple's gatekeeping policy – and apply a difference-in-differences analysis that uses the Android app developers (who are not affected by the jailbreak) as a control group.

5.2 Theoretical Background

5.2.1 Access Control and Safeguards from Information Frictions

An important part of corporate-level decision making is carefully managing the access to critical assets of production, both within and outside the boundaries of the firms (Ouchi, 1979; Ouchi & Dowling, 1974). In interfirm and other value chain relationships, research has identified the implications of granting some form of access to resources that often become essential (Speckbacher *et al.*, 2015; Tiwana & Keil, 2007). Managing access for outside parties is associated with two inter-related issues of organizational governance: On one hand, it provides firms with "power to regulate" transactions on the basis of controlling critical assets of production. For a firm to play a regulatory role in transactions, autonomous agents and other firms need to consent to be subjected to the governance rules; they will likely do so only when the private benefits are superior to the alternatives. On the other hand, when controlling access, firms need to be diligent about likely exposure to hazards from information asymmetry including potential misappropriation of critical assets when transacting with partners (Benner & Zenger, 2016; Leiblein *et al.*, 2002; Reuer, 2009). Prior research in strategy and organizational studies have examined how organizational governance mechanisms alleviate hazards originating from asymmetric information. One important insight in this literature is that all such de-hazarding mechanisms are costly and it is better to have safeguards in place *ex ante* prior to the transactions compared to relying on *ex post* solutions (Reuer, 2009; Williamson, 1975). When protecting a naïve or uninformed party, an ounce of prevention truly is worth a pound of cure. Thus, the ability to control access gives firms an important tool to preemptively evaluate any potential information related challenges.

In digital organizations facilitated by two sided platforms, access control becomes even more salient as platforms often manage fuzzy and incomplete contractual relationships with complementors, yet the value creation and appropriation depends on "who" opts to participate and "what" is collectively done in the marketplace (Adner, 2017; Adner *et al.*, 2019; Liebeskind, 1996). It is often not easy for platform owners to predict in advance which complementors will participate in their marketplace (Tiwana, 2013). For example, the value proposition of Apple's App Store depends on what types of app publishers are in the platform and what products they decide to offer. Since each of them has potential to change the iPhone into a different product than it was ever originally envisioned to be, it may be difficult to predict what apps get submitted to the App Store given the "open invitation" from Apple, and perhaps equally difficult to predict what apps and what features within apps will attract demand from users.

5.2.2 Gatekeeping and Digital Organizations

In digital organizations, a prominent way platforms execute their "power to regulate" is by controlling access through gatekeeping. Although some platforms exploit this regulatory power by capturing rents in exchange for granting more favorable access to some complementors, they must also balance this rent seeking incentive against the need to provide the kind of "level playing field" that is necessary to induce a wide range of different complementors to create value for the platform. Gatekeeping policies thus give platforms a governance tool to control access by granting appropriate complementors and their products access, based on weighing their own interests against the perceived interests of both sides of the market (Tiwana, 2013; Zhang *et al.*, 2020).

Compared to more conventional intermediaries in the offline world, online digital platforms often have better (digital) tools at their disposal to conduct more effective gatekeeping.

For example, by setting up coordination protocols for the developer and user to interact with each other, platform owner becomes distinctly knowledgeable about the interactions among parties on both sides. Platforms' superior capabilities in making sense of large-scale data generated through interactions on the platform (including ratings, reviews, and other feedback mechanisms) also enhance their gatekeeping function. In this regard, online gatekeeping in digital platforms has the potential to give users a level of quality assurance that may be superior to what an offline warranty or certification screening can provide.

Similarly, as platform owners send an "open invitation" to participate in the platform, they shift part of the product development cost and risk to complementors whose concerns about the quality may be varied and inconsistent, which gives platform owners an incentive to exert quality control in order to preserve and protect the overall user experience on the platform. While this can certainly also be true for offline intermediaries as well, the digital nature of online products, services, and interactions can usually make quality concerns more urgent/transparent, and thereby make the gatekeeping exercised by digital platforms more rigorous compared to their analog counterpart firms.

However, an offline firm or intermediary making assessments about granting access in interfirm or some other value chain relationships is usually focused on a small and selective set of potential partners, while the gatekeeping function on a digital platform – especially one that gives an open public invitation to complementors – must prepare for the possibility of doing a large volume of screening. For these reasons, online platform gatekeeping may be more costly than its offline counterpart, especially for any parts of the screening process that cannot easily be automated or scaled up through technology.

5.2.3 Platform Complementors and Value Appropriation

Profit-motivated complementors are unlikely to develop new products for a platform without having appropriate mechanisms to protect their innovations and enable them to capture value from them. How intellectual property protections and appropriability regimes operate can have substantial effect on the strategic choices made by the innovator (Teece, 1986; Teece, 2006). Weak appropriability regimes lead to decreased investments in new product developments and makes it harder to profit from innovation (Figueiredo & Teece, 1996; Pisano, 2006). A viable appropriability regime emerges from the alignment between how the value chain is organized to protect innovation and how the innovator's assets of production are positioned.

In two-sided platforms, complementary products are often not well-protected by the regular intellectual property apparatus. For example, if other complementors can offer similar products, or even direct copies, a focal innovator is worse off in terms of potential value appropriation opportunities. The subtle and relatively tacit nature of creating digital products and services that are appealing to users makes it harder to extend conventional intellectual property protections. As supply-side complementors lack conventional intellectual property protections when developing applications in platforms, alternative approaches, such as platform gatekeeping, may facilitate their value appropriation endeavors (Boudreau, 2012; Helfat & Raubitschek, 2018; Teece, 2018).

5.3 Hypotheses

5.3.1 Interplay between Platform Gatekeeping and Profiting from Innovation

Information-related challenges can be substantial in platforms that intermediate transactions between two-sides of the market with little or no prior direct relationships, nor any necessary expectation of future interactions. Every transaction, online or otherwise, requires some level of safeguards that can alleviate the problems caused by asymmetric information between the transacting partners. A platform-based organization can be successful only when both sides of the market find it to be an effective mode of transacting compared to the alternatives (Adner, 2017). Therefore, as the designer of the marketplace, it is often incumbent upon the platform to provide suitable mechanisms to reduce the problems caused by information asymmetry.

How platform gatekeeping is designed and executed can significantly affect the informational and transactional environment of the platform organizations. We consider platform gatekeeping to be primarily a screening mechanism deployed by the platform owner to create suitable conditions for both sides to conduct their exchanges. Particularly, it allows platforms to weed out perceived unfit complementors *ex ante* and curate a set of others to grant access. To do so, platform owners create criteria to decide what is allowed and who is allowed in the marketplace.[4] In this paper, we focus on an exogenous event that weakens the gatekeeping policy which was intended to be strong. The change in the gatekeeping regime diminishes the platform owner's ability to screen apps that would otherwise be unauthorized.

Joining the literatures of organizational governance and profiting from innovation, we maintain that access control in the form of platform gatekeeping protects value appropriation prospects of supply-side complementors. We argue that strong platform gatekeeping provides an internal regulatory solution by restricting access to entrants who imitate or copy market-proven complementary products in terms of functionalities, user interface and other features (Parker &

[4] These criteria may be predetermined and explicit, or they may be implicit, ad hoc, and formulated "on the fly" in response to particular cases, or some combination of both. For example, in Apple iOS platform the following predetermined reasons are used for rejecting apps: crashes and bugs, intellectual property infringement broken links, existence of place-holder content, incomplete information, inaccurate descriptions, misleading users, substandard user interface and repeated submission of similar apps (Apple, 2017). However, iOS guidelines also use more tacit forms of gatekeeping for rejecting apps. Apple articulates it as follows; "We will reject apps for any content or behavior that we believe is over the line. What line, you ask? Well, as a Supreme Court Justice once said, 'I'll know it when I see it.' And we think that you will also know it when you cross it." (Apple, 2020).

Van Alstyne, 2018; Wang *et al.*, 2018; Zhang *et al.*, 2020). Similarly, platform gatekeeping also safeguards authorized complementors against low quality offerings that can contaminate the supply-side pool. In doing so, it reduces the intensity of competition among supply-side complementors leading to the overall quality increase in the platform. This, in turn, increases the attractiveness of the platform (Casadesus-Masanell & Hałaburda, 2014; Halaburda *et al.*, 2018). For supply-side complementors concerned about the aspects of weak property rights in digital platform both from technical and legal standpoint, a strong platform gatekeeping provides credible assurances on realizing a "realistic revenue architecture" and protect rent streams from innovation (Pisano, 2006; Teece, 2010).

From the users' perspective, strong platform gatekeeping provides a preventative *ex ante* screening mechanism to protect against a variety of hazards that can be embedded in a complementor's digital products, such as malware, privacy-invading features, and interference with operating system features or with digital products from other complementors (Belleflamme & Peitz, 2019a; Casadesus-Masanell & Hałaburda, 2014; Tiwana, 2013). In the absence of such strong gatekeeping, users face a difficult adverse selection problem (Akerlof, 1970; Halaburda *et al.*, 2018), which can threaten to derail the realization of value proposition in platforms and, in extreme cases, may lead to the failure of the two-sided market altogether. Attracting users without the *ex ante* preventative screening solution provided by platform gatekeeping may then require complementors to offer the second-best alternative of *ex post* remedial solutions in which users can conduct their own individual screening – e.g., "try before you buy" monetization methods like freemium or initial free trial.

From the platform's perspective, it may be quite costly, labor-intensive, and time-consuming to execute gatekeeping activities (especially on a large platform like the iOS App Store, with over 2 million apps), yet it can nevertheless be in the platform's interests to do so, in order to ensure the long-term growth and sustainability of its value proposition. After all, supply-side complementors will only make investments in innovation that benefit the platform's value proposition when they have adequate assurances on their ability to appropriate value from those investments (Adner, 2017; Adner *et al.*, 2019; Boudreau, 2017). In this regard, the interests of a platform are at least partially aligned with those of its complementors, since the platform's ability to appropriate value *from* its marketplace depends upon ensuring its complementors' ability to appropriate value *within* that marketplace. Although gatekeeping may be expensive for a platform to implement, it can nevertheless be an effective part of the solution for helping complementors to appropriate value, thereby incentivizing them to continue their innovations and to stay engaged with the platform, for two parallel reasons: First, platform gatekeeping prevents a complementor's intellectual property from being misappropriated by other complementors (e.g., preventing other complementors from distributing products that violate its copyrights or trademarks). In the absence of platform gatekeeping to prevent intellectual property right violations *ex ante*, a complementor would have to rely on the threat of litigation to remedy intellectual property right violations *ex post* – a much slower, more expensive, and less reliable solution, which would therefore discourage complementors from making the kind of costly and risky investments in innovation that would benefit the platform.[5] Second, as mentioned earlier, gatekeeping also gives users a warranty-like *ex ante* assurance about the absence of hazards (risk of adverse selection), which increases users' willingness to pay for complementors' products, thereby allowing complementors to appropriate

[5] For example, in the case of Google vs. Oracle America, United States Supreme Court had ruled that copied codes from Oracles API user interface are "inherently bound together with uncopyrightable ideas (the overall organization of the API) and the creation of new creative expression", therefore legally unenforceable. Similarly, highly similar products being offered in the platform, it reduces the prospects to profit from innovation for the focal innovator. In such externally weak appropriability regimes, platform owner tends to step up and leverage their power to regulate to provide alternative protections internally through governance mechanisms such as platform gatekeeping.

value more easily – even before actually experiencing them – without the threat of market failure due to adverse selection. Indeed, compared to more indirect *ex post* monetization methods like freemium, initial free trial, or advertising-based revenue, complementors may prefer such a direct *ex ante* monetization because it offers a relatively more predictable revenue from each user, while also requiring less effort to implement.

Taken together, both of these benefits to the overall value proposition of its marketplace – i.e., the prevention of both intellectual property rights violations and adverse selection hazards – may help motivate a platform to devote the necessary time, effort, and expense for gatekeeping. Moreover, the second benefit may also both enable and motivate complementors to appropriate value through more *ex ante* monetization methods. Thus, we hypothesize:

> ***Hypothesis 1:*** *Weakening of platform gatekeeping will decrease complementors' use of direct ex ante monetization methods.*

5.3.2 Platform Gatekeeping, Increased Effort and Indirectly Profit from Innovation

When platform gatekeeping is weak, users wary of potential intellectual property rights violations and adverse selection problems will have to resort to their own screening in lieu of the screening that gatekeeping would otherwise provide. Platform screening is more efficient than user screening at least for three reasons. First, platforms' screening activities benefit from scale economies because platforms can leverage general rules and other suitable heuristics to make assessments about both individual and classes of complementors reducing the unit cost of screening. Second, platform screening need only be done once, rather than requiring each user to do his or her own individual screening. Third, platform screening benefits from the platform owner's superior data, data analysis skills, and capabilities to assess technical issues – all of which are derived from platform owners' access to vast collection of data about complementors and users. These benefits include, for example, pattern recognition algorithms to detect structural anomalies in the apps or fraudulent documentation and predictive tools to foresee problematic future behaviors. Therefore, for all three of these reasons, user screening is a second-best solution from the user's perspective.

User screening is also a second-best solution from a high-quality supply-side complementor's perspective, because users are inefficient at screening. Naturally, a user is likely to be less willing to pay a complementor while she is still evaluating the quality of its product, which can make monetization slower and less predictable. So, complementors must make extra efforts and investments to signal quality, possibly leading to increased use of *ex post* monetization methods like freemium, initial free trial, or advertising-based revenue. *Ex post* indirect methods are inferior and their prospects to monetize can be slow and unpredictable, so supply-side complementor will only resort to preferring them when *ex ante* direct methods fail. Thus, we hypothesize:

Hypothesis 2: *Weakening of platform gatekeeping will increase complementors' use of indirect ex post monetization methods.*

5.3.3 Role of Portfolio Diversity

Research on corporate portfolio diversity suggests that single-business or relatively less diversified firms have both less "access to investment from cross-subsidization" and less flexibility to respond in changing business conditions (Palich *et al.*, 2000). For example, such firms might be limited in their ability to shift critical assets of production between businesses within its portfolio or possess slack resources that could be redeployed within the organizations in such contingencies (Levinthal & Wu, 2010; Sakhartov & Folta, 2015). When a firm is well diversified, it allows the corporate office to optimize the allocation of resources among several businesses by taking a “bird eye’s” view on the overall firm. Teece (1980) suggested portfolio diversity as a mechanism for “capturing integration economies associated with the simultaneous supply of inputs common to a number of production processes geared to distinct final product markets”. Integration economies are often achieved by better flexibility of diversified to move the resources from slow-growing or static segments of the organization to more robust and commercially successful segments that may require additional investments (Palich *et al.*, 2000). Such flexibilities, combined with firm-specific assets that cannot be sold in external factor markets due to transaction costs and other imperfections, provide diversified firms internal market efficiencies when the corporate decisions are executed well and coordination costs are kept low (Markides, 1992; Zhou, 2011).

Taken together, firms with high portfolio diversity tend to have integration economies allowing them to respond to shocks faster and make them more adaptable to changes. In platform organizations, supply-side complementors with high portfolio diversity may react in a faster and flexible fashion to the information-related challenges to profit from their innovation that come from weaker gatekeeping. Thus, we hypothesize:

> ***Hypothesis 3:*** *Complementors’ portfolio diversity will strengthen the negative relationship between the weakening of platform gatekeeping and complementors’ use of direct ex ante monetization methods.*

5.4 Data And Methods

5.4.1 Research Design and Identification Strategy

To study our proposed hypotheses, we focus on mobile app platforms that enable transactional relationships between mobile app publishers and users. We exploit the exogenous lapse in gatekeeping in Apple iOS 10 platform due to "jailbreak". Apple's iOS platform is one of the two leading platforms for mobile apps, along with Google's Android platform. The iOS jailbreak is a hacking procedure that provides root access to the iOS operating system and removes built-in iOS security restrictions. It allows users to install applications that are not officially approved by the iOS review process. The Apple iOS platform implements a strong gatekeeping with the end-user software licensing agreement advising heavily against jailbreak (Mollick, 2016).[6] However, given the restrictive nature of Apple's iOS platform, jailbreaking has also created a substantial underground developer community (e.g., Cydia) focusing on providing free pirated versions of approved apps, as well as other apps and operating system modifications that are unavailable in the iOS App Store. Jailbreaks thus create substantial challenges to officially approved iOS application developers, since their innovation can be closely imitated or outright stolen by underground developers. Furthermore, approved iOS developers may also be harmed because the operation or effectiveness of their apps can be disrupted by unauthorized apps, especially those containing malware, that are installed on jailbroken iPhones (Tiwana, 2013; Zhang *et al.*, 2020). When such a disruption occurs, the user of the jailbroken device simply observes a failure of an official authorized app, and is likely to be completely unaware that the problem is actually due to interference by an *unauthorized* app, in which case the user may understandably believe that the authorized app suffers from quality problems. Consequently, the contaminated environment created by the jailbreak event creates adverse selection problems between users and mobile app developers. As such, jailbreak provides a suitable context to study our proposed hypotheses on the

[6] Apple suggests the following with regard to jailbreak: "iOS is designed to be reliable and secure from the moment you turn on your device. Built-in security features protect against malware and viruses and help to secure access to personal information and corporate data. [..] Apple strongly cautions against installing any software that hacks iOS. It is also important to note that unauthorized modification of iOS is a violation of the iOS end-user software license agreement" (Apple, 2021).

implications of gatekeeping for complementors' value appropriation strategies.

The jailbreak of iOS 10 provides a unique quasi-natural experimental setting to fit our analyses – it was unexpected since this particular version of iOS was especially built to withstand usual jailbreak techniques used by hackers. The popular Apple weblog iDownloadBlog called the potential jailbreak of iOS 10 an "ongoing wait" and reported that the extended uncertainty about whether it could be jailbroken was "continu[ing] to rattle the minds of hobbyists and tweak developers alike" (iDownloadBlog, 2016). As months passed, the iDownloadBlog pondered whether "another jailbreak actually [will] see the light". In fact, iOS 10 took the longest time (i.e., 99 days) for hackers to jailbreak compared to the previous 9 jailbreaks (with previous mean and median of 20.3 and 9 days, respectively).[7] This longer window also gives us enough time to observe any adjustments that supply-side complementors made with regard to their value appropriation strategies, both before and after the jailbreak treatment.

In our difference-in difference empirical design, we compare the iOS app developers (treatment group) with the Android app developers in the competing platform (control group) before and after the jailbreak. Following Zhang *et al.* (2020), we use Android app developers as a control in our design, since Android developers are generally comparable to iOS developers in turns of skillset and their apps are unaffected by the jailbreak event that is specific to iOS. Using Android developers as a control also allows us to create cross platform comparison that can capture any systemic trend in the overall platform economy (Mayzlin *et al.*, 2014). After constructing the full sample, we also conduct coarsened exact matching (CEM) to build a matched sample between

[7] Two prominent hacking teams with expertise on jailbreak, Pangu Team and evad3rs were unable to make progress as Apple made substantial security upgrades in iOS 10 to close off the usual tactics to jailbreak using security vulnerabilities. It look an 18-year old student Luca Todesco to execute a series of complex procedures to execute the jailbreak of iOS 10.

iOS and Android app developers to reduce model dependency, causal estimation error, imbalance, and other systematic biases (Blackwell *et al.*, 2009; Iacus *et al.*, 2012).[8]

5.4.2 Sample Construction

We obtained the data from a leading app analytics firm in the mobile app industry for all the iOS Apple App Store and Android Google Play store apps in the U.S., where both platforms together nearly exhaust the market with over 99% of the market share. To construct the base sample, we considered incumbent app publishers who had produced at least one new app during the sampling window from September 16, 2015 to the day before iOS 10's release date of September 12, 2016. This filer is used to identify the active app publishers prior to the subsequent observation window. We also removed any app publisher that has produced more than 25 apps during the observation window (e.g., Internet giants such as Facebook). In sum, our unit of analysis is app publisher by week, supported by a panel-structured dataset with iOS and Android app publishers.

We considered an observation window of 27 weeks – 13 weeks before and 13 weeks after the treatment, and during the treatment week – from September 18, 2016 and April 1, 2017. This creates a weekly panel data set before and after the jailbreak event on December 28, 2016. The observation window of thirteen weeks is selected to be comparable to the app development cycles observed in the prior literature (Kuk, 2006; Zhang *et al.*, 2020). We restrict our sample to the app developers who had at least one newly released app in the observation window and whose apps were captured in performance measures such as revenue or ranking in the subsequent year for at least 60 days. This is to ensure that our sample is comprised of apps that have a business orientation

[8] CEM provides an effective solution to address limitations of other matching methods by "guarantee(ing) that the imbalance between the matched treated and control groups will not be larger than the *ex ante* user choice" (Iacus *et al.*, 2012).

and are not developed by individual hobbyists or amateurs for other purposes such as personal or intellectual satisfaction (Boudreau, 2012). After these screens, our sample is comprised of 3,569 iOS and 10,742 Android app developers.

In a final step, we conducted CEM matching. This step helps us to improve the covariate balance between the treatment and control groups on all covariates that might affect the value appropriation strategies of app developers up to a year before iOS 10 release to identify the historic patterns. By dropping dissimilar observations, our CEM-matched sample is comprised of 3,538 iOS and 9,706 Android app developers.

5.4.3 Variables and Measurement

Dependent Variables. To measure app publishers' direct monetization from users suggested in H1, we use *Paid Count*, measured as the number of paid new apps published by an iOS or Android app publisher in a given week. We focus on new apps published by app developers, rather than updates to existing apps, given our focus on how developers create and profit from innovation.

We utilize two different variables to capture app publishers' indirect monetization from users to test H2 and triangulate our findings. First, we use *Freemium Count*, measured as the number of free apps with the option for subsequent purchase after experiencing the product (i.e., in-app purchase) published by an iOS or Android app publisher in a week. Second, we use *Advertisement Count*, measured as the number of advertisement supported apps published by an iOS or Android app publisher in a week.

Explanatory Variables. The quasi-experimental design facilitates a difference-in-differences (DD) analysis. The first indicator variable used in the DD analysis is *iOS*, identified by a dummy variable indicating the platform where the publisher is associated with (*iOS = 1* if it is an iOS publisher, *iOS = 0* if an Android publisher). The other indicator variable is *After*, which identifies the period after the jailbreak event (*After* = 1 for the weeks after jailbreak, *After* = 0 for the weeks before jailbreak). The interaction term *iOS x After* (DD) is then created to identify the treatment effect of weakened gatekeeping on direct (H1) and indirect means (H2) of monetization.

Testing of H3 requires a measure of portfolio diversity of app publishers. Extant research has highlighted the importance of portfolio diversity for complementors in platform research as well as for firms in corporate strategy research more broadly (Chen *et al.*, 2020a; Hitt *et al.*, 1994; Wu, 2013). For example, in platforms literature, scholars have observed that portfolio diversity can affect new product performance (Chen *et al.*, 2020a). To test our prediction that app publishers with high portfolio diversification in their products are more concerned about the implications of weak gatekeeping on the strategies to profit from innovation, we use *Portfolio Diversity*, measured by the number of different market segments in which an app publisher participates. We use the 23 app categories defined by the iOS platform to create a comparable set from the 48 app categories in Android.[9]

Control Variables. We also include several variables to control for app publisher attributes that may cause changes in the conditional expectation of outcomes between the treatment and control groups. We control for the number of apps with age restriction (*Age Restriction)*. We include the number of game apps (*Game Apps)* for all the app developers in a week, as developing game apps might require different skills compared to other apps, which in turn may affect the variance in the dependent variable (Cennamo & Santalo, 2013; Chen *et al.*, 2020b). In addition,

[9] Details are available upon request. (Need to add a bit more information here about how the comparable set is created, and then say "details are available upon request.")

prior research on platform governance and more broadly in corporate strategy suggests that publisher characteristics such as age (*Publisher Age*) and portfolio size indicating the number of apps a publisher has in its portfolio (*Publisher Portfolio Size*) may affect its ability to appropriate value. An important consideration for app publishers is to multi-home and develop apps for both iOS and Android platforms. Multi-homing often indicates both the capabilities and skills of app developers (i.e., ability to develop apps for multiple platforms) (Tiwana, 2013) and their strategic decision making (i.e., for strategic reasons such as diversifying risk and expanding the market reach) (Bakos & Halaburda, 2020; Belleflamme & Peitz, 2019b). As such, multi-homing may affect the value appropriation mechanisms of supply-side complementors. Thus, we include *Multi-homing* measured as the total number of multi-homing apps in the portfolio of an app publisher.

Finally, we include a full set of app publisher-level fixed effects to capture any time-invariant and unobserved characteristics of app publishers. We also include a full set of week fixed effects to control for any systematic time-varying economic and other conditions that may affect complementors' strategies to profit from innovation. By doing so, we cannot incorporate the main effects of *iOS* and *After* due to the perfect collinearity with both publisher-level and week fixed effects. Table 1 reports the descriptive statistics and correlations.

5.4.4 Estimation Approach.

We estimated linear regression models using the DD technique to test whether the weakened gatekeeping (due to jailbreak) will affect complementors' strategies to directly and indirectly profit from innovation (H1 and H2), and whether portfolio diversity of the publisher strengthens these effects (H3).

5.5 Results

5.5.1 Analysis of DD Assumptions

A key assumption in DD research designs is that, the parallel trend between treated (iOS) and control (Android) samples must hold (Angrist & Pischke, 2008), meaning if not for the iOS 10 jailbreak, both samples would have followed parallel paths before and after the shock. This assumption cannot be rejected in our analysis. First, we used the data before the jailbreak event (13 weeks prior to the event) and tested whether the treated iOS sample and control Android sample would follow a similar parallel path until the point of treatment. As shown in Table 2, we found insignificant interaction terms between the linear time trend variable and the *iOS* platform dummy, indicating that the parallel trend assumption cannot be rejected.

Second, we tested for the Ashenfelter's dip by splitting the pre-treatment sample into two subsamples, -13 weeks to -7 weeks prior to the jailbreak as one subsample and -6 weeks to -1 week prior to the jailbreak. We tested whether there is any significant difference in the DD coefficient between the treated iOS sample and control Android sample. As we show in Table 3, we don't find any difference, indicating that the main regression results we find through DD analysis (to be reported below) are not due to a sudden shift in the period leading up to the shock.

5.5.2 Main Results

Moving to results of hypotheses tests, Column 1 in Table 4 reports results of DD regressions that test for hypothesis 1 (H1) for the dependent variable *Paid Count*. In H1, we posit that an exogenous lapse in platform gatekeeping (weakened gatekeeping) will decrease supply-side complementors using direct monetization methods of *ex ante* value appropriation. As shown in Column 1 (CEM sample), we find a negative and highly significant coefficient ($p<0.001$) on the DD variable (*iOS*After*), providing strong support for this hypothesis. This result shows that iOS app publishers witness a 33.2 percent decrease ($p < 0.001$) in the number of paid new apps being released after jailbreak, compared to Android app developers.

Hypothesis 2 (H2) tests how the weakening of platform gatekeeping will require complementors to increase their use of indirect monetization methods and increase their effort to profit from innovation *ex post*. Columns 1 and 2 (CEM sample) in Table 5 report results of DD regressions that test for hypothesis 2 (H2) for two dependent variables *Freemium Count* and *Advertisement Count*. We find a positively and significant coefficient on the DD variable (*iOS*After*) ($p = 0.06$ and $p < 0.001$, respectively), supporting H2's prediction. The results indicate that iOS app publishers witness a 33.2 percent increase in the number of freemium apps and a 71.4 percent increase in the number of advertisement-supported apps being released after jailbreak, compared to Android app developers.

Hypothesis 3 (H3) identifies an important boundary condition under which the exogenous change in gatekeeping that results in weak platform gatekeeping will have a greater or smaller effect on *Paid Count*. Specifically, H3 predicts that the portfolio diversity of supply-side complementors will positively moderate the DD variable such that the main effect in H1 is stronger among complementors with greater portfolio diversity. Consistent with this prediction, the triple-DD term (*DD*Portfolio Diversity*) is positive and significant ($p < 0.01$) in Column 2 of Table 4.

5.5.3 Supplementary Analyses

We conducted several analyses to examine the robustness of our results and broaden our understanding of the findings and the underlying mechanisms. First, we considered the full sample in Columns 3 and 4 of Table 2 for H1 and H3, and in Columns 3 and 4 of Table 2 for H2. We continue to find qualitatively similar results, indicating the robustness of our results to both unmatched and CEM matched samples.

Second, we create an alternative to the count dependent variables used in the main analysis. Specifically, we consider the dummy counterparts for each of them. *Paid Dummy* is used as an alternative measure for testing H1; it is a dummy variable that takes a value 1 when a publisher publishes at least one paid app in a week, and 0 otherwise. In a similar vein, we create *Freemium Dummy* and *Advertisement Dummy* to test H2. In Tables 6 and 7, we find qualitatively similar results to main analysis on both CEM matched and unmatched full samples.

Third, to further elucidate how weak gatekeeping will require complementors to reduce their reliance on direct *ex ante* monetization methods and increase reliance on indirect *ex post* monetization methods, we study whether app publishers releasing paid apps without in-app purchases changes after the jailbreak. To do so we create, *Paid App without In-App Purchase*, measured as the total number of paid apps without in-app purchase option published by an app publisher in a week. In Table 8 Columns 1 - 2, we find the DD coefficient to be negative and significant. It indicates that complementors not only reduce their direct *ex ante* monetization methods such as producing paid apps, they also are hesitant to do so without the in-app purchase option that gives users an opportunity to experience.

5.6 Discussion

5.6.1 Research Contributions

This study makes several research contributions. First, our study joins emerging research linking platform-based organizations with corporate strategy research on organizational governance (Adner, 2017; Adner *et al.*, 2019; Chu & Wu, 2021; McIntyre & Srinivasan, 2017). Corporate strategy examines how managers can facilitate the process of value creation and appropriation by organizing and overseeing the scope of their firms. In platform-based organizations, complementors on both sides of the market are critical for a value proposition to materialize; yet organizing them is challenging for at least two reasons. First, complementors are often loosely aligned with the platform and not contractually or hierarchically bound as in traditional firms (Kretschmer *et al.*, 2020). Second, the overall scope of the platforms depends on "who" participates and "what" is being collectively done in the marketplace. If corporate strategy mechanisms are what make the corporate whole more valuable than the sum of the individual parts of it (Feldman, 2019; Porter, 1989), how does it manifest in platform-based organizations? In this paper, we focus on an important corporate-level tension in platform-based markets: How can platform owners harness the innovation that complementors offer, while exerting enough control over the overall process to protect users and preserve the quality of the overall user experience? We show that platform gatekeeping, an important corporate-level decision, can be an important control mechanism to facilitate the complementors' value appropriation from their innovative products. As such, this paper offers new ideas on how platform gatekeeping shapes the dynamics between supply-side complementors and users, indicating a promising direction for future platform research.

For complementary relationships to work successfully in an extended period of time, there needs to be a viable "appropriability regime" that enables comprehensive strategies to profit from innovation (Pisano, 2006; Teece, 1986; Teece, 2010). As Lippman and Rumelt (2003) articulated in their "payments perspective", profit-motivated complementors will make their valuable resources available to a focal firm only if they are compensated adequately for doing so. In platform-based digital organizations, value appropriation of complementors is fundamentally shaped by the interactions with relevant market players and their competitive incentives. It is vital for platform owners, as they orchestrate the participation of complementors, to design a marketplace that has appropriate safeguards from information frictions. By focusing on how the interplay between platform governance and complementor monetization strategies is affected by information-related challenges, we contribute a more nuanced understanding of value appropriation in multi-stakeholder environments.

Third, this study contributes to the emerging stream of research about how the effectiveness of particular monetization mechanisms may differ depending on organizational and transactional characteristics (Casadesus-Masanell & Zhu, 2013; Teece, 2018; Zott & Amit, 2008). As corporate-level governance mechanisms create contingencies on how value proposition works in platform organizations, it is vital to understand under what conditions certain monetization methods would be suitable for supply-side complementors to deploy. Although research has articulated some theory about relevant contingency factors influencing monetization mechanisms, empirical evidence remains scant. Casadesus-Masanell and Zhu (2013) articulated this challenge as follows: "The lack of empirical studies on this question is most likely due to the difficulty in collecting data on possible business model implementations that did not happen.... While empirically testing... using a large sample dataset seems a daunting, if not impossible, task given the difficulty involved in data collection...." The large and novel dataset utilized in this study, combined with its quasi-experimental design, provides an opportunity to study how one important contingency factor, platform gatekeeping, influences the relative effectiveness of monetization methods. Consequently, we contribute to this literature by providing empirical evidence, as well as a new perspective to think about platform governance and monetization methods comparatively.

5.6.2 Limitations and Future Research

Several limitations in this study point to future research directions. First, although we found that weak gatekeeping affects complementor strategies to profit from innovation, we have limited our focus to such monetization methods as direct sales, advertiser support and freemium most relevant to mobile apps. Future work should consider other monetization methods such as subscriptions, which are prominent in other platforms (e.g., Spotify, Netflix). In addition, while we recognized the heterogeneity of supply-side complementors by studying the moderating effect of portfolio diversity, other features of app publishers may also affect their strategies to profit from innovation. Finally, due to data limitations, we couldn't directly observe whether specific gatekeeping choices would affect platform market effectiveness. It would be a vital addition to the literature to study platform market effectiveness directly. We leave those extensions for future research.

5.7 Conclusion

Platform owners play an important governance role to align complementors towards orchestrating a value proposition for users in the presence of asymmetric information. In this paper, we join corporate strategy and organizational governance research with the emerging study of platform-based organizations, and argue that platform owners can leverage gatekeeping as a governance instrument to mitigate information asymmetry and shape complementors' strategies to profit from innovation. By exploiting the iOS 10 jailbreak to Apple's gatekeeping policy, we show that weak gatekeeping creates challenges to the viability of complementors' appropriability regimes. We particularly highlight how platform gatekeeping can mitigate adverse selection problems and how it can provide a screening device to the platform owners *ex ante* to restrict access to unsuited complementors. As platform-based organizations take a prominent role in the digitally transformed economy, we hope that our paper will stimulate further interest in corporate strategy and organizational governance of platforms and other forms of digital marketplaces. In particular, we hope it will create interest in understanding the implications of platform governance on innovation and complementors pursuing to profit from it.

5.8 References

Adner R. 2017. Ecosystem as Structure: An Actionable Construct for Strategy. *Journal of Management* **43**(1): 39-58.

Adner R, Puranam P, Zhu F. 2019. What Is Different About Digital Strategy? From Quantitative to Qualitative Change. *Strategy Science* **4**(4): 253-261.

Akerlof GA. 1970. The Market for 'Lemons': Qualitative Uncertainty and the Market Mechanism. *Quarterly Journal of Economics* **84**: 488-500.

Angrist JD, Pischke J-S. 2008. *Mostly Harmless Econometrics: An Empiricist's Companion*. Princeton university press.

Apple. 2017. Avoiding Common App Rejections. https://developer.apple.com/app-store/review/#common-app-rejections.

Apple. 2020. App Store Review Guidelines. https://developer.apple.com/app-store/review/guidelines/ (06-15-2020.

Apple. 2021. Unauthorized Modification of Ios Can Cause Security Vulnerabilities, Instability, Shortened Battery Life, and Other Issues.

Bakos Y, Halaburda H. 2020. Platform Competition with Multihoming on Both Sides: Subsidize or Not? *Management Science* **66**(12): 5599-5607.

Baldwin CY, Woodard CJ. 2009. The Architecture of Platforms: A Unified View. *Platforms, markets and innovation* **32**.

Barney JB. 2018. Why Resource-Based Theory's Model of Profit Appropriation Must Incorporate a Stakeholder Perspective. *Strategic Management Journal* **39**(13): 3305-3325.

Belleflamme P, Peitz M. 2019a. Managing Competition on a Two-Sided Platform. *Journal of Economics & Management Strategy* **28**(1): 5-22.

Belleflamme P, Peitz M. 2019b. Platform Competition: Who Benefits from Multihoming? *International Journal of Industrial Organization* **64**: 1-26.

Benner MJ, Zenger T. 2016. The Lemons Problem in Markets for Strategy. *Strategy Science* **1**(2): 71-89.

Blackwell M, Iacus S, King G, Porro G. 2009. Cem: Coarsened Exact Matching in Stata. *The Stata Journal* **9**(4): 524-546.

Boudreau K. 2010. Open Platform Strategies and Innovation: Granting Access Vs. Devolving Control. *Management Science* **56**(10): 1849-1872.

Boudreau K. 2012. Let a Thousand Flowers Bloom? An Early Look at Large Numbers of Software App Developers and Patterns of Innovation. *Organization Science* **23**(5): 1409-1427.

Boudreau KJ. 2017. Platform Boundary Choices & Governance: Opening-up While Still Coordinating and Orchestrating. *Entrepreneurship, Innovation, and Platforms. Advances in Strategic Management* **37**: 227-297.

Boudreau KJ, Hagiu A. 2009. Platform Rules: Multi-Sided Platforms as Regulators. *Platforms, Markets and Innovation* **1**: 163-191.

Casadesus-Masanell R, Zhu F. 2013. Business Model Innovation and Competitive Imitation: The Case of Sponsor-Based Business Models. *Strategic Management Journal* **34**(4): 464-482.

Casadesus-Masanell R, Hałaburda H. 2014. When Does a Platform Create Value by Limiting Choice? *Journal of Economics & Management Strategy* **23**(2): 259-293.

Cennamo C, Santalo J. 2013. Platform Competition: Strategic Trade-Offs in Platform Markets. *Strategic management journal* **34**(11): 1331-1350.

Chen L, Wang M, Cui L, Li S. 2020a. Experience Base, Strategy-by-Doing and New Product Performance. *Strategic Management Journal*.

Chen L, Yi J, Li S, Tong T. 2020b. Platform Governance Design in Platform Ecosystems: Implications for Complementors' Multihoming Decision.

Chu LY, Wu B. 2021. Designing Online Platforms for Customized Goods and Services: A Market-Frictions Based Perspective. *Academy of Management Review*(ja).

Evans DS, Schmalensee R. 2016. *Matchmakers: The New Economics of Multisided Platforms*. Harvard Business Review Press.

Feldman E. 2019. Corporate Strategy: Past, Present and Future. *Strategic Management Review*.

Figueiredo JMd, Teece DJ. 1996. Mitigating Procurement Hazards in the Context of Innovation. *Industrial and Corporate Change* **5**(2): 537-559.

Halaburda H, Jan Piskorski M, Yıldırım P. 2018. Competing by Restricting Choice: The Case of Matching Platforms. *Management Science* **64**(8): 3574-3594.

Helfat CE, Raubitschek RS. 2018. Dynamic and Integrative Capabilities for Profiting from Innovation in Digital Platform-Based Ecosystems. *Research Policy* **47**(8): 1391-1399.

Hitt MA, Hoskisson RE, Ireland RD. 1994. A Mid-Range Theory of the Interactive Effects of International and Product Diversification on Innovation and Performance. *Journal of management* **20**(2): 297-326.

Iacus SM, King G, Porro G. 2012. Causal Inference without Balance Checking: Coarsened Exact Matching. *Political analysis*: 1-24.

iDownloadBlog. 2016. Ios 10 Jailbreak: The Ongoing Wait.

Isaacson W. 2011. *Steve Jobs*. Simon & Schuster: New York.

Kapoor R, Agarwal S. 2017. Sustaining Superior Performance in Business Ecosystems: Evidence from Application Software Developers in the Ios and Android Smartphone Ecosystems. *Organization Science* **28**(3): 531-551.

Kapoor R, Teece DJ. 2021. Three Faces of Technology's Value Creation: Emerging, Enabling, Embedding. *Strategy Science* **6**(1): 1-4.

Kretschmer T, Leiponen A, Schilling M, Vasudeva G. 2020. Platform Ecosystems as Meta-Organizations: Implications for Platform Strategies. *Strategic Management Journal*.

Kuk G. 2006. Strategic Interaction and Knowledge Sharing in the Kde Developer Mailing List. *Management science* **52**(7): 1031-1042.

Leiblein MJ, Reuer JJ, Dalsace F. 2002. Do Make or Buy Decisions Matter? The Influence of Organizational Governance on Technological Performance. *Strategic Management Journal* **23**(9): 817-833.

Levinthal DA, Wu B. 2010. Opportunity Costs and Non-Scale Free Capabilities: Profit Maximization, Corporate Scope, and Profit Margins. *Strategic Management Journal* **31**(7): 780-801.

Liebeskind JP. 1996. Knowledge, Strategy, and the Theory of the Firm. *Strategic management journal* **17**(S2): 93-107.

Lippman SA, Rumelt RP. 2003. The Payments Perspective: Micro-Foundations of Resource Analysis. *Strategic Management Journal* **24**(10): 903-927.

Markides CC. 1992. Consequences of Corporate Refocusing: Ex Ante Evidence. *Academy of Management journal* **35**(2): 398-412.

Mayzlin D, Dover Y, Chevalier J. 2014. Promotional Reviews: An Empirical Investigation of Online Review Manipulation. *American Economic Review* **104**(8): 2421-2455.

McIntyre DP, Srinivasan A. 2017. Networks, Platforms, and Strategy: Emerging Views and Next Steps. *Strategic Management Journal* **38**(1): 141-160.

Mollick E. 2016. Filthy Lucre? Innovative Communities, Identity, and Commercialization. *Organization Science* **27**(6): 1472-1487.

Ouchi WG. 1979. A Conceptual Framework for the Design of Organizational Control Mechanisms. *Management science* **25**(9): 833-848.

Ouchi WG, Dowling JB. 1974. Defining the Span of Control. *Administrative Science Quarterly*.

Palich LE, Cardinal LB, Miller CC. 2000. Curvilinearity in the Diversification–Performance Linkage: An Examination of over Three Decades of Research. *Strategic management journal* **21**(2): 155-174.

Parker G, Van Alstyne M. 2018. Innovation, Openness, and Platform Control. *Management Science* **64**(7): 3015-3032.

Pisano G. 2006. Profiting from Innovation and the Intellectual Property Revolution. *Research Policy* **35**(8): 1122-1130.

Porter M. 1989. From Competitive Advantage to Corporate Strategy. In *Readings in Strategic Management.* Springer.

Porter ME. 1996. What Is Strategy? *Harvard Business Review* **74**(6): 61-78.

Reuer JJ. 2009. Organizational Economics Insights from Acquisitions Research. In *Economic Institutions of Strategy. Advances in Strategic Management.* Emerald Group Publishing Limited.

Sakhartov AV, Folta TB. 2015. Getting Beyond Relatedness as a Driver of Corporate Value. *Strategic Management Journal* **36**(13): 1939-1959.

Speckbacher G, Neumann K, Hoffmann WH. 2015. Resource Relatedness and the Mode of Entry into New Businesses: Internal Resource Accumulation Vs. Access by Collaborative Arrangement. *Strategic Management Journal* **36**(11): 1675-1687.

Tadelis S. 2016. Reputation and Feedback Systems in Online Platform Markets. *Annual Review of Economics* **8**: 321-340.

Teece D. 1980. Economies of Scope and the Scope of the Enterprise. *Journal of Economic Behavior and Organization* **1**: 223-247.

Teece DJ. 1986. Profiting from Technological Innovation: Implications for Integration, Collaboration, Licensing, and Public Policy. *Research Policy* **15**(6): 285-305.

Teece DJ. 2006. Reflections on "Profiting from Innovation". *Research policy* **35**(8): 1131-1146.

Teece DJ. 2010. Business Models, Business Strategy and Innovation. *Long Range Planning* **43**(2-3): 172-194.

Teece DJ. 2018. Profiting from Innovation in the Digital Economy: Enabling Technologies, Standards, and Licensing Models in the Wireless World. *Research Policy* **47**(8): 1367-1387.

Tiwana A. 2013. *Platform Ecosystems: Aligning Architecture, Governance, and Strategy*. Newnes.

Tiwana A, Keil M. 2007. Does Peripheral Knowledge Complement Control? An Empirical Test in Technology Outsourcing Alliances. *Strategic Management Journal* **28**(6): 623-634.

Wang Q, Li B, Singh PV. 2018. Copycats Vs. Original Mobile Apps: A Machine Learning Copycat-Detection Method and Empirical Analysis. *Information Systems Research* **29**(2): 273-291.

Williamson OE. 1975. *Markets and Hierarchies: Analysis and Antitrust Implications*. The Free Press: New York.

Wu B. 2013. Opportunity Costs, Industry Dynamics, and Corporate Diversification: Evidence from the Cardiovascular Medical Device Industry, 1976–2004. *Strategic Management Journal* **34**(11): 1265-1287.

Zhang Y, Li J, Tong TW. 2020. Platform Governance Matters: How Platform Gatekeeping Affects Knowledge Sharing among Complementors. *Strategic Management Journal*.

Zhou YM. 2011. Synergy, Coordination Costs, and Diversification Choices. *Strategic Management Journal* **32**(6): 624-639.

Zhu F, Furr N. 2016. Products to Platforms: Making the Leap. *Harv. Bus. Rev.* **94**(4): 72-78.

Zott C, Amit R. 2008. The Fit between Product Market Strategy and Business Model: Implications for Firm Performance. *Strategic Management Journal* **29**(1): 1-26.

Table 5.1 Descriptive Statistics and Correlations

	Variables	Mean	S.D	Min	Max	1	2	3	4	5	6	7	8	9
1	Paid App Count	0.01	0.12	0	9	1.00								
2	Freemium Count	0.02	0.14	0	1	**0.01**	1.00							
3	Ad Supported Count	0.01	0.11	0	5	**0.01**	**0.35**	1.00						
4	Portfolio Diversity	3.09	2.65	1	21	**0.03**	**0.03**	0.01	1.00					
5	Age Restriction	0.06	0.28	0	12	**0.37**	**0.5**	**0.38**	**0.01**	1.00				
6	Game Apps	0.03	0.20	0	9	**0.16**	**0.54**	**0.37**	**0.07**	**0.65**	1.00			
7	Multi-homing	0	0.05	0	2	**0.06**	**0.12**	**0.09**	**0.01**	**0.15**	**0.11**	1.00		
8	Age	129.6	91.21	16	469	**0.00**	**0.01**	**0.02**	**0.28**	**0.02**	**0.03**	**0.01**	1.00	
9	Portfolio Size	31.37	93.70	1	4752	**0.02**	**0.01**	**0.01**	**0.16**	**0.06**	**0.05**	**0**	**0.12**	1.00

Note: N = 344,329 representing the CEM matched sample. All bold values are significant.

Table 5.2 Test for Parallel Trend in the Pre-Treatment Period

Variables	Paid Count	Freemium Count	Advertisement Count
iOS*Week	0.000342	0.000151	0.000546
	(0.000175)	(0.000215)	(0.000232)
Controls	Yes	Yes	Yes
Observations	172,157	172,157	172,157
Week FE	Yes	Yes	Yes
Publisher FE	Yes	Yes	Yes

Note: Standard errors clustered at the app publisher level are reported in parentheses.

Table 5.3 Test for Ashenfelter Dip in the Pre-Treatment Period

Variables	Paid Count	Freemium Count	Advertisement Count
DD (iOS*After)	0.000772	0.00199	0.000063
	(0.000902)	(0.001)	(0.001)
Controls	Yes	Yes	Yes
Observations	172,157	172,157	172,157
Week FE	Yes	Yes	Yes
Publisher FE	Yes	Yes	Yes

Note: Standard errors clustered at the app publisher level are reported in parentheses.

Table 5.4 DD Regression Results for the Direct Monetization of Complementors

Variables	(1)	(2)	(3)	(4)
	CEM Sample		Full Sample	
	Paid Count	Paid Count	Paid Count	Paid Count
DD (iOS * After)	**-0.00332*****	0.000196	**-0.00485*****	-0.000668
	(-4.16)	(0.14)	**(-5.17)**	(-0.48)
DD * Portfolio Diversity		**-0.00104***		**-0.00114****
		(-2.56)		**(-3.12)**
Portfolio Diversity	-0.000519	0.000284	-0.00222*	-0.00136
	(-0.65)	(0.31)	(-2.45)	(-1.40)
Age Restriction	0.201***	0.201***	0.234***	0.233***
	(17.09)	(17.07)	(14.92)	(14.89)
Game Apps	-0.0788***	-0.0787***	-0.0744**	-0.0741**
	(-5.87)	(-5.86)	(-3.16)	(-3.15)
Multi-homing	0.00869	0.00883	-0.0631***	-0.0631***
	(0.58)	(0.59)	(-3.54)	(-3.53)
Age	-0.0000424	-0.0000548	0.000123	0.000107
	(-0.74)	(-0.97)	(1.51)	(1.32)
Portfolio Size	0.0000404	0.0000438	0.00000577	0.0000154
	(0.46)	(0.50)	(0.08)	(0.22)
Constant	0.00789	0.00694	-0.00821	-0.00919
	(1.23)	(1.07)	(-0.81)	(-0.90)
Observations	344,329	344,329	368,310	368,310
Week FE	Yes	Yes	Yes	Yes
Publisher FE	Yes	Yes	Yes	Yes

Note: This table reports results for the baseline and moderation hypotheses. Columns 1-2 report results busing the CEM sample. Columns 3-4 report results using the full sample. Columns 1 and 3 report results for H1, Columns 2 and 4 report for H3. The unit of analysis is the publisher-week level. All models include publisher and week fixed effects. In the columns, *iOS* variable is dropped out due to perfect collinearity with the fixed effects. Standard errors clustered on publisher level are reported in parentheses. *p* values reported in the text are based on two-tailed test.

Table 5.5 DD Regression Results for the Indirect Monetization of Complementors

	(1)	(2)	(3)	(4)
	CEM Sample		Full Sample	
Variables	Freemium Count	Advertisement Count	Freemium Count	Advertisement Count
DD (iOS * After)	**0.00168**	**0.00714*****	**0.00378*****	**0.00651*****
	(1.87)	**(7.32)**	**(3.91)**	**(11.64)**
Portfolio Diversity	0.00133**	0.00353***	0.00236***	0.00273***
	(2.58)	(7.00)	(4.43)	(7.41)
Age Restriction	0.130***	0.0975***	0.105***	0.438***
	(25.14)	(18.30)	(21.94)	(15.09)
Game Apps	0.268***	0.117***	0.239***	0.223***
	(24.23)	(13.14)	(19.60)	(6.03)
Multi-homing	0.112***	0.0575***	0.0936***	0.307***
	(7.16)	(3.97)	(6.36)	(8.34)
Age	0.0000516	0.00000812	-0.0000872	-0.000118***
	(0.91)	(0.16)	(-1.44)	(-3.62)
Portfolio Size	-0.0000332	-0.000122***	0.0000551	-0.0000167
	(-0.79)	(-3.97)	(1.34)	(-1.36)
Constant	-0.00375	-0.0000792	0.0105	0.0144***
	(-0.56)	(-0.01)	(1.36)	(3.44)
Observations	344,329	344,329	368,310	368,310
Week FE	Yes	Yes	Yes	Yes
Publisher FE	Yes	Yes	Yes	Yes

Note: This table reports results for H3. Columns 1-2 report results using the CEM sample. Columns 3-4 report results using the full sample. The unit of analysis is the publisher-week level. All models include publisher and week fixed effects. In the columns, *iOS* variable is dropped out due to perfect collinearity with the fixed effects. Standard errors clustered on publisher level are reported in parentheses. *p* values reported in the text are based on two-tailed test.

Table 5.6 DD Regression Results for H1 and H3 with *Paid Dummy* as Dependent Variable

Variables	(1)	(2)	(3)	(4)
	CEM Sample		Full Sample	
	Paid Dummy	Paid Dummy	Paid Dummy	Paid Dummy
DD (iOS * After)	**-0.00280*****	0.000721	**-0.00332*****	0.00157
	(-3.96)	(0.75)	**(-4.16)**	(1.68)
DD * Portfolio Diversity		**-0.00104*****		**-0.00116*****
		(-4.12)		**(-5.21)**
Observations	344,329	344,329	368,310	368,310
Week FE	Yes	Yes	Yes	Yes
Publisher FE	Yes	Yes	Yes	Yes

Note: This table reports results for the baseline and moderation hypotheses with *Paid App Dummy as dependent variable*. Columns 1-2 report results busing the CEM sample. Column 3-4 report results using the full sample. Column 1 and 3 report results for H1, Columns 2 and 4 report for H3. The unit of analysis is the publisher-week level. All models include publisher and week fixed effects. In the columns, *iOS* variable is dropped out due to perfect collinearity with the fixed effects. Standard errors clustered on publisher level are reported in parentheses. *p* values reported in the text are based on two-tailed test.

Table 5.7 DD Regression Results for H2 with *Freemium Dummy and Ad Dummy* as Dependent Variables

	(1)	(2)	(3)	(4)
	CEM Sample		Full Sample	
Variables	Freemium Dummy	Advertisement Dummy	Freemium Dummy	Advertisement Dummy
DD (iOS * After)	**0.00378***** **(3.91)**	**0.00651***** **(11.64)**	**0.00168** **(1.87)**	**0.00452***** **(10.10)**
Observations	344,329	344,329	368,310	368,310
Week FE	Yes	Yes	Yes	Yes
Publisher FE	Yes	Yes	Yes	Yes

Note: This table reports results for H3. Columns 1-2 report results using the CEM sample. Column 3-4 report results using the full sample. The unit of analysis is the publisher-week level. All models include publisher and week fixed effects. In the columns, *iOS* variable is dropped out due to perfect collinearity with the fixed effects. Standard errors clustered on publisher level are reported in parentheses. *p* values reported in the text are based on two-tailed test.

Table 5.8 Summary of DD Regression Using *Paid App without In-App Purchase* as Dependent Variable

Variables	(1) CEM Sample Paid App without In-App Purchase	(3) Full Sample Paid App without In-App Purchase
DD (iOS * After)	**-0.00231*****	**-0.00200****
	(-3.49)	**(-2.93)**
Controls	Yes	Yes
Observations	344,329	368,310
Week FE	Yes	Yes
Publisher FE	Yes	Yes

Note: Standard errors clustered on publisher level are reported in parentheses. *p* values reported in the text are based on two-tailed test.